REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)* 05-09-2014	**2. REPORT TYPE**	**3. DATES COVERED** *(From - To)*

4. TITLE AND SUBTITLE

Analyzing and Assessing Brain Structure with Graph Connectivity Measures

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

McGlaughlin, Alec Scott

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U.S. Naval Academy
Annapolis, MD 21402

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

Trident Scholar Report no. 430 (2014)

12. DISTRIBUTION / AVAILABILITY STATEMENT

This document has been approved for public release; its distribution is UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Recent studies have shown that graph theory is a useful tool in studying changes in brain connectivity resulting from degenerative conditions such as Alzheimers disease (AD). The human brain can be naturally modeled as a network and graph theory measures enable the connectivity properties of these models to be quantified. These measures allow differences in connectivity between brains with and without signs of dementia to be identified. This study is an investigation of methods used to create network models from magnetic resonance imaging (MRI) data and the impact of these methods on connectivity measures. We tested previous network creation methods and newly developed methods, in combination with connectivity measures to determine which combinations yielded the most reliable identification of dementia severity. We categorized dementia severity using four diagnostic groups: healthy older adults who maintained normal cognition for 36 months, individuals with Mild Cognitive impairment (MCI) who remained MCI for 36 months, individuals who started the study with MCI but developed AD within 36 months (MCI-AD), and individuals with AD. We modeled connectivity between brain regions using correlations between regional cortical thickness measurements obtained using MRI. Our results suggest that different graph measures change in an ordered fashion for the structural brain network as an individual develops AD and may be useful as early-diagnosis tools.

15. SUBJECT TERMS

Network Modeling, Alzheimer's disease, Dementia, Graph Theory, MRI

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**		127	**19b. TELEPHONE NUMBER** *(include area code)*

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

U.S.N.A. --- Trident Scholar project report; no. 430 (2014)

ANALYZING AND ASSESSING BRAIN STRUCTURE WITH GRAPH CONNECTIVITY MEASURES

by

Midshipman 1/c Alec S. McGlaughlin
United States Naval Academy
Annapolis, Maryland

Certification of Adviser(s) Approval

Associate Professor David J. Phillips
Mathematics Department

Acceptance for the Trident Scholar Committee

Professor Maria J. Schroeder
Associate Director of Midshipman Research

USNA-1531-2

Abstract

Recent studies have shown that graph theory is a useful tool in studying changes in brain connectivity resulting from degenerative conditions such as Alzheimers disease (AD). The human brain can be naturally modeled as a network and graph theory measures enable the connectivity properties of these models to be quantified. These measures allow differences in connectivity between brains with and without signs of dementia to be identified.

This study is an investigation of methods used to create network models from magnetic resonance imaging (MRI) data and the impact of these methods on connectivity measures. We tested previous network creation methods and newly developed methods, in combination with connectivity measures to determine which combinations yielded the most reliable identification of dementia severity. We categorized dementia severity using four diagnostic groups: healthy older adults who maintained normal cognition for 36 months, individuals with Mild Cognitive impairment (MCI) who remained MCI for 36 months, individuals who started the study with MCI but developed AD within 36 months (MCI-AD), and individuals with AD. We modeled connectivity between brain regions using correlations between regional cortical thickness measurements obtained using MRI.

Our results suggest that different graph measures change in an ordered fashion for the structural brain network as an individual develops AD and may be useful as early-diagnosis tools.

Keywords

Network Modeing, Alzheimer's disease, Dementia, Graph Theory, MRI

Acknowledgements

Foremost, I would like to express my sincere gratitude to the Trident Scholar Research Committee for providing me the opportunity to undertake this research project. I would like to thank Professor Schroeder for her unwaivering support of my research and tireless work with all the Trident researchers to ensure that we stayed on track and had the resources we needed to make our projects a success. Further, I would like to thank Don Garner and Linda Adlum for their support and expertise with the parallel computational resources provided by the research office at USNA.

My sincerest thanks also go to Professor David Phillips, my primary advisor, for his continuous support of my research. His patience and enthusiasm were crucial in keeping me motivated through the summer and the following academic year. I cannot thank him enough for all of the valuable research and personal lessons that he has taught me during our time working together.

I would also like to thank my external advisor Professor Anja Soldan of the Johns Hopkins University. Her support and guidance during my internship over the summer were crucial in getting my research up and running. In addition, I am sincerely grateful for the research opportunity that the Johns Hopkins Department of Cognitive Neuroscience provided me during my summer internship.

Additionally, I would like to thank our collaborators, CDR Dave Ruth of USNA and Professor Leah Jager of the Johns Hopkins University, for their support and advice throughout our research.

Last but not least, I would like to thank my family: my parents Ron and Ann McGlaughlin as well as my sister Caitlin McGlaughlin for their unwavering support throughout my life.

Contents

Analyzing and assessing brain structure with graph connectivity measures

Trident Final Report for ACYEAR 2013-2014
Alec McGlaughlin

1 Introduction

Timely assessment of brain structure and function is an important subject in the fight against brain disorders such as Alzheimer's Disease (AD) and dementia. Our research focuses on the investigation of structural connectivity patterns in the brain through the use of network models.

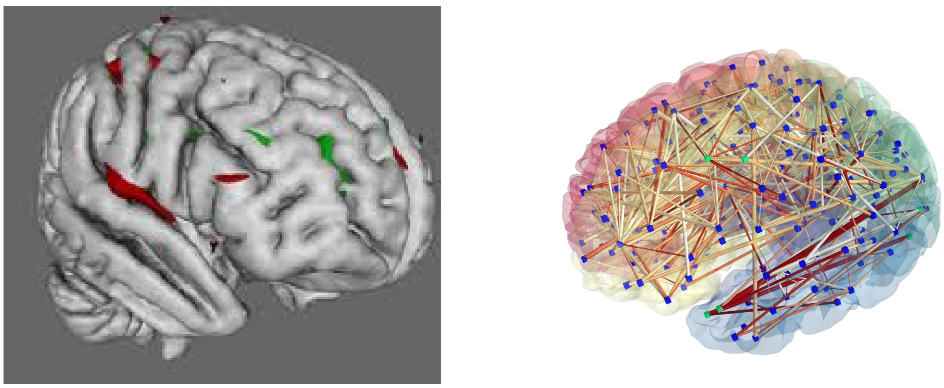


Figure 1: A 3-D image of the human brain constructed from Structural MRI (left) and a brain image with a network model superimposed (right).

In our project, we model the brain as a combination of distinct regions which are physically connected to one another. These connections between regions of the brain are important as they allow communications between the different regions, allowing the regions to work together to enable an individual to function. A natural way to model the brain in this manner is using a network (also referred to as a graph). In figure 1, the network image models the regions of the brain as blue and green squares. We refer to the blue and green squares as the **nodes** of our network. Furthermore, regions that are physically connected to each other are connected by a line segment which we call **edges** in our network. The different edge colors indicate the relative strength of the connection between regions. The networks we create in our project are derived from data taken from images using Structural Magnetic Resonance Imaging (Structural MRI) which will be further discussed in Section 2.1.

We are interested in how the nodes of this network are connected because these connections reflect the communication between regions in the brain. Through the examination of how the regions in our model are connected, we can make inferences about how regions in the brain are communicating and how effectively they are communicating. We examine changes in the cerebral cortex, i.e., the outermost layer of soft matter in the brain, to discover certain patterns of change across regions. We believe that communication between brain regions is different in healthy individuals and individuals suffering from Alzheimer's disease, and that disease progression is reflected by patterns of structural change in the cerebral cortex [7].

As a result of our project, we hope to develop models and early diagnosis tools based on networks to combat Alzheimer's disease. In addition, our research in modeling the brain is applicable to other brain related issues such as traumatic brain injury (TBI).

In order to make comparisons between healthy and diseased brains, we needed to quantify the characteristics of our network models. We provide mathematical definitions of these measures in Section 2.2 and describe them intuitively here. We implement several connectivity measures used in previous studies which used networks to analyze brain structure in order to reproduce results from these previous studies. These studies have focused mainly on measures of connectivity which are sensitive to small perturbations in the network [12, 11, 8, 3]. One of the most popular measures, *characteristic path length*, focuses on how many intermediate regions communication must pass through between two regions which are not directly connected. Essentially, it is a measure of distance between two communicating regions. As such, even removing one edge between two regions can significantly impact the measure. Another measure, *clustering coefficient*, measures the tendency of a network to form local cliques, with high *clustering coefficient* reflecting strong local connectivity [13].

In our study, we also implement more global measures of connectivity. The first measure we utilize is *Fiedler value* which is a measure of how well different regions in the brain are connected with each other. This measure focuses on the whole network rather than examining specific regions. A higher *Fiedler value* indicates more robust connections between regions of the brain, while decreases in *Fiedler value* indicate a degraded level of connectivity. We also implement *normalized Fiedler value* which, like *Fiedler value*, is a measure of the robustness of communication between regions of the brain. Unlike *Fiedler value*, however, *normalized Fiedler value* will not necessarily increase with increases in network size (i.e. increases in the number of regions directly connected to each other). In this way, it is a measure of the effectiveness of the setup of the network. A higher *normalized Fiedler value* indicates a more efficient structural connectivity between regions of the brain. In addition, we calculate *assortativity* which measures interaction between highly connected regions of the brain or hub regions. Highly connected hub regions are regions which are directly connected to a large number of other regions. A high *assortativity* indicates that highly connected regions of the brain tend to be connected to each other. As noted above, we provide technical definitions of these measures in Section 2.2.

2 Background

This section provides insight into the technical processes and procedures of this project in addition to discussing relevant previous work. Section 2.1 addresses the brain imaging technology used to gather data to create structural and functional network models. Section 2.2 provides rigorous mathematical definitions for the terminology and metrics associated with network creation and analysis. Finally, Section 2.3 discusses relevant previous studies utilizing graph theory and network models to analyze the brain.

2.1 Imaging Modalities

Magnetic Resonance Imaging (MRI) and Diffusion Tensor Imaging (DTI) are two imaging techniques used to assess brain structure. The two types of MRI used in brain studies are structural MRI and functional MRI. Structural MRI provides an in-depth image of the physical structure of the brain which is useful in the creation of structural brain networks, i.e. determining which regions of the brain are physically connected. Meanwhile, functional MRI (fMRI) yields an image of regions of oxygenated versus deoxygenated blood in the brain and is useful in determining which regions of the brain often function together to create functional brain networks. Deoxygenated regions signal brain activity, as activity consumes oxygen, and as a result the deoxygenated vs. oxygenated image produced by fMRI is a map of which parts are of the brain are active and which are not at a given time. In creating functional networks, regions of the brain which often activitate together, i.e., often show up on fMRI as deoxygenated regions together, are considered connected. DTI allows the diffusion of water from regions in the brain to be mapped. These diffusion patterns are of particular interest when investigating brain structure as they depict the white matter tracts in the brain which are the connecting fibers between grey matter regions. These fibers are important in structural networks as they are physical connections in the brain.

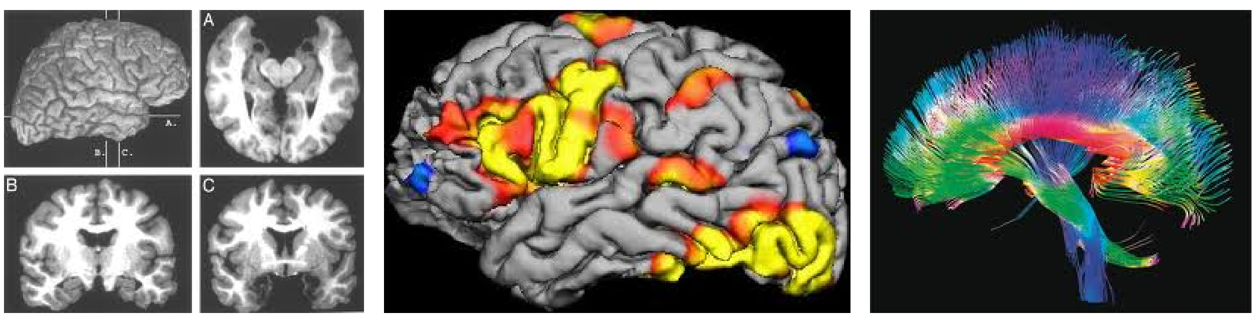


Figure 2: Examples of structural MRI (left), fMRI (center), and DTI images.

Another modality that has been used in the study of brain function is magnetoencephalography (MEG) which records the magnetic fields produced by electrical currents in the brain. The resulting images and data from these modalities can be used as the basis for creating graph networks of the brain. Graph theory methods and techniques can then used to analyze the networks.

2.2 Network Definitions

A graph $G = (N, E)$ consists of a set N of nodes and a set $E \subset NxN$ of edges which indicate relationships between pairs of nodes. For an edge (i, j), we define $(i, j) = (j, i)$ and for all nodes $i \in N$ we assume $(i, i) \notin E$. Two sample graphs, G_1 and G_2 are shown below in Figures 4 and 5 with each having a node set $\{1, 2, 3, 4, 5, 6, 7\}$. However, G_1 has the edge set

$$\{(1, 2), (1, 3), (2, 4), (3, 4), (3, 5), (4, 6), (5, 6), (5, 7)\}$$

whereas G_2 has the edge set

$$\{(1, 3), (1, 5), (2, 4), (2, 6), (3, 4), (3, 5), (4, 6), (5, 7)\}.$$

We define a *network* as a graph whose edges have associated numerical values or weights. Regions of the brain can be modeled as nodes in a network. These nodes can be determined based on assumptions made prior to the collection of data, or derived from the data. We define networks derived from data as *data-driven networks* and these will be the concentration of this study. Nodes which are connected by an edge are called *adjacent*. A path is an ordered sequence of nodes in which no node repeats and consecutive nodes in the sequence are connected by an edge belonging to the graph. For example, $6-5-3-1$ is a path in G_1 but not a path in G_2 as the edge $(5,6)$ is in G_1 but not G_2. Two nodes are *connected* if the graph contains at least one path from one node to the other, e.g., all pairs of nodes in both G_1 and G_2 are connected. A graph is said to be *connected* if every pair of its nodes is connected. A connected graph is $k-$connected if k is the minimum number of edges that can be removed and cause the graph to no longer be connected.

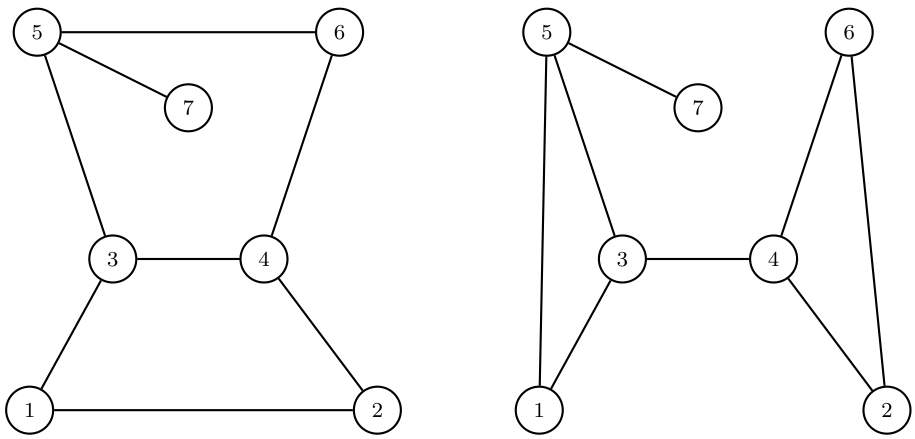


Figure 3: Example graphs G_1 (left) and G_2

Once a network is established, graph measures can be used to quantify the properties and connectivity of the network. In addition to k-connectivity, some connectivity measures include average *node degree*, d_i, which is the number of nodes adjacent to a single node, i; the *shortest path* between any two nodes in the graph, which we define as the smallest number of edges needed to move from one node to the other node; and *betweenness centrality* which is the number of shortest paths that include a given node.

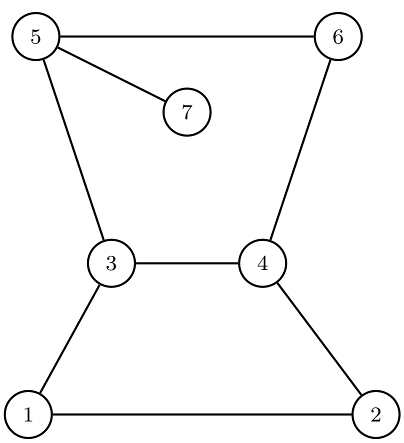
In contrast to studies which focus on local measures, we also include connectivity measures which are less sensitive to local perturbations in addition to more localized measures. Two local measures we examine are *characteristic path length* and *clustering coefficient*. We define the characteristic path length of a graph, G, as the average of the shortest paths between all pairs of nodes in G [13].

The clustering coefficient [13] of a graph ,G, is defined as $\sum_j \sum_{k>j} (\frac{(w_(i,j) + w_(i,k)}{2})A$.

Two measures that we examine in our study that are less sensitive to local perturbations are the *Fiedler value*, and *assortativity*, which we now define. The Fiedler value [6], also known as the *algebraic connectivity*, is the second smallest *eigenvalue* of the *Laplacian matrix* of a graph, which is the *adjacency matrix* subtracted from the *degree matrix* of the graph. Given n nodes in a graph, the degree matrix, $D_{i,j}$, is an $n \times n$ matrix with $D_{i,j} = d_i$ if $i = j$, and zero otherwise. The adjacency matrix, $A_{i,j}$ is an $n \times n$, matrix with $A_{i,j}$ equal to the edge weight of (i, j) if (i, j) belongs to the set of edges and zero otherwise. In an unweighted graph, i.e., a graph with no edge weights, $A_{i,j} = 1$ if (i, j) belongs to the set of edges and zero otherwise. The Laplacian matrix, L, is defined as $L = D - A$. An eigenvector of a square matrix B is a vector x such that there is a value λ where $Bx = \lambda x$. The value λ is called an eigenvalue of B. Since symmetric real matrices always have real eigenvalues [9], λ will always be a real number. The Fiedler value is the second smallest eigenvalue of the Laplacian matrix.

Because the Fiedler value is weakly increasing in the number of edges in a graph, we are also interested in the Fiedler value of the *normalized Laplacian* [4]. The normalized Laplacian, $\mathcal{L}$ is defined as $\mathcal{L}_{i,j} = L_{i,j}/\sqrt{d_i d_j}$. The Fiedler value for the normalized Laplacian is again the second smallest eigenvalue.

The Randić index [10] of a graph, G, is defined as $S_\alpha(G) = \sum_{(i,j)\in E} (d_i d_j)^\alpha$. We define the assortativity as the Randić index with $\alpha = 1$.

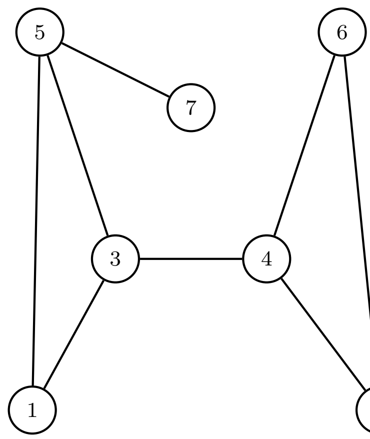


$$\begin{pmatrix} 2 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & 2 & 0 & -1 & 0 & 0 & 0 \\ -1 & 0 & 3 & -1 & -1 & 0 & 0 \\ 0 & -1 & -1 & 3 & 0 & -1 & 0 \\ 0 & 0 & -1 & 0 & 3 & -1 & -1 \\ 0 & 0 & 0 & -1 & -1 & 2 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$$

$$\begin{pmatrix} 1.00 & -0.50 & -0.41 & 0 & 0 & 0 & 0 \\ -0.50 & 1.00 & 0 & -0.41 & 0 & 0 & 0 \\ -0.41 & 0 & 1.00 & -0.33 & -0.33 & 0 & 0 \\ 0 & -0.41 & -0.33 & 1.00 & 0 & -0.41 & 0 \\ 0 & 0 & -0.33 & 0 & 1.00 & -0.41 & -0.58 \\ 0 & 0 & 0 & -0.41 & -0.41 & 1.00 & 0 \\ 0 & 0 & 0 & 0 & -0.58 & 0 & 1.00 \end{pmatrix}$$

Figure 4: A graph, G_1, with its Laplacian and normalized Laplacian. The characteristic path length is 1.9048, the clustering coefficient is 0, the assortativity is 73, the Fiedler value is 0.6086 and the normalized Fiedler value is 0.3649.

Both G_1 and G_2 have the same degree sequence, i.e., the degrees of individual nodes do not change from G_1 to G_2. Also, both graphs are *one-connected* in that node 7 is attached to the rest of the graph by only one arc. Despite identical degree sequences, the graphs have very different Fiedler values and assortativity values. In particular, G_1 has a Fiedler value of 0.6086 and a normalized Fiedler value of 0.3649, with an assortativity value of 73. Meanwhile, G_2 has a Fiedler value of 0.3404, a normalized Fiedler value of 0.1697, and an assortativity value of 49. The higher values for G_1 are reflective of the fact that G_1 has more redundant paths between nodes than G_2. The graphs also have very different clustering coefficients, with G_1 having a clustering coefficient of 0, while G_2 has a clustering coefficient of 0.5714. Characteristic path length also differs between the two graphs as G_1 has characteristic path

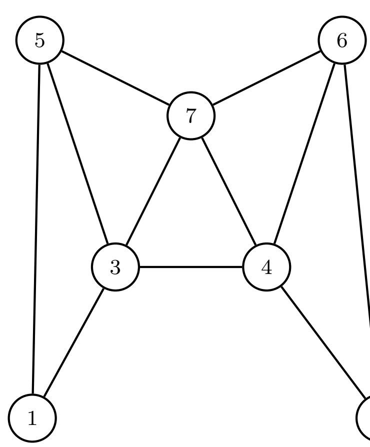


$$\begin{pmatrix} 2 & 0 & -1 & 0 & -1 & 0 & 0 \\ 0 & 2 & 0 & -1 & 0 & -1 & 0 \\ -1 & 0 & 3 & -1 & -1 & 0 & 0 \\ 0 & -1 & -1 & 3 & 0 & -1 & 0 \\ -1 & 0 & -1 & 0 & 3 & 0 & -1 \\ 0 & -1 & 0 & -1 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$$

$$\begin{pmatrix} 1.00 & 0 & -0.41 & 0 & -0.41 & 0 & 0 \\ 0 & 1.00 & 0 & -0.41 & 0 & -0.50 & 0 \\ -0.41 & 0 & 1.00 & -0.33 & -0.33 & 0 & 0 \\ 0 & -0.41 & -0.33 & 1.00 & 0 & -0.41 & 0 \\ -0.41 & 0 & -0.33 & 0 & 1.00 & 0 & -0.58 \\ 0 & -0.50 & 0 & -0.41 & 0 & 1.00 & 0 \\ 0 & 0 & 0 & 0 & -0.51 & 0 & 1.00 \end{pmatrix}$$

Figure 5: A graph, G_2, with its Laplacian and normalized Laplacian. The characteristic path length is 2.0476, the clustering coefficient is 0.5714, the assortativity is 49, the Fiedler value is 0.3404, and the normalized Fiedler value is 0.1697. G_2 has the same degree sequence as G_1.

length 1.9048 while G_2 has characteristic path length 2.0476.



$$\begin{pmatrix} 2 & 0 & -1 & 0 & -1 & 0 & 0 \\ 0 & 2 & 0 & -1 & 0 & -1 & 0 \\ -1 & 0 & 4 & -1 & -1 & 0 & -1 \\ 0 & -1 & -1 & 4 & 0 & -1 & -1 \\ -1 & 0 & -1 & 0 & 3 & 0 & -1 \\ 0 & -1 & 0 & -1 & 0 & 3 & -1 \\ 0 & 0 & -1 & -1 & -1 & -1 & 4 \end{pmatrix}$$

$$\begin{pmatrix} 1.00 & 0 & -0.35 & 0 & -0.41 & 0 & 0 \\ 0 & 1.00 & 0 & -0.35 & 0 & -0.41 & 0 \\ -0.35 & 0 & 1.00 & -0.25 & -0.29 & 0 & -0.25 \\ 0 & -0.35 & -0.25 & 1.00 & 0 & -0.29 & -0.25 \\ -0.41 & 0 & -0.29 & 0 & 1.00 & 0 & -0.29 \\ 0 & -0.41 & 0 & -0.29 & 0 & 1.00 & -0.29 \\ 0 & 0 & -0.25 & -0.25 & -0.29 & -0.29 & 1.00 \end{pmatrix}$$

Figure 6: A graph, G_3, with its Laplacian and normalized Laplacian. The characterstic path length is 1.619, the clustering coefficient is 0.905, the assortativity is 124, the Fiedler value is 0.9139, and the normalized Fiedler value is 0.3596.

In Figure 6, G_3 is shown, which is G_2 with the arcs $(3, 7)$ and $(4, 7)$ added to it. Because of the added edges the Fiedler value of G_3 is 0.9139. However, the normalized Fiedler value is only 0.3596 which is less then that of G_1, reflecting that G_1 seems to have greater "per-edge" connectivity.

As our investigation progressed, we began to explore the implications of creating "optimal networks" by investigating the biological significance of maximizing a given connectivity measure. For example, we closely investigated the definition of clustering coefficient to determine the physical implications for a structural brain network having a high, versus a low, clustering coefficient. We began our investigation by completing the following proof to show that in order to achieve the maximum clustering coefficient (i.e. a clustering coefficient of 1), a graph must be complete. That is, each node must be adjacent to every other node. We assumed that the graph was connected as we only deal with connected graphs in this project resulting from our implementation of the breadth first search algorithm mentioned in Section 3.3.

2.2.1 Clustering Coefficient Bound

It is known that the clustering coefficient of a complete graph is one. We provide a strict bound on the clustering coefficient of a connected graph that is not complete.

Property 1. *The clustering coefficient of a connected graph is strictly less than one if the graph is not complete.*

Proof. Assume a graph, G, is connected but not complete. Denote the clustering coefficient of G by CC_G. Now, assume that the clustering coefficient of G satisfies $CC_G = 1$. Let the number of nodes in G equal n. Since G is not complete $\exists$ a node, n_1, such that the unweighted degree of n_1, $d_(n_1)$, is less than the maximum degree for a node, i.e., $d_(n_1) < n - 1$. Now, let N be the set of nodes adjacent to n_1. Then $\exists n_2$, a node in N, with set of adjacent nodes M s.t. $M \nsubseteq N$. This implies $\exists$ node $n_3 \in M$ and $n_3 \notin N$. Let A be the adjacency matrix for graph G. Since by definition clustering coefficient is equal to $\sum_j \sum_{k>j} (\frac{(w_(i,j) + w_(i,k)}{2})A$. We have $CC_{n2} < 1$, a contradiction since for the clustering coefficient of the graph to be one, the clustering coefficient of each node must equal one. Therefore the clustering coefficient of G is less than 1. $\square$

2.3 Previous Work

Previous studies have shown that *network connectivity* differs between healthy people and those suffering from dementia [5, 12, 11, 8, 3]. Two network types, structural and functional, have been the focus of several recent studies on brain functioning [5, 12, 11, 8, 3]. Adjacency between regions in the two types of networks differs, however, with structural networks reflecting the physical construction of the brain, i.e. the regions of grey matter with white matter connections. Adjacency in structural networks can be established using correlations between parameters measured from the Structural MRIs, such as cortical thickness [8]. Structural networks can also be established based on the diffusion patterns from DTI data, which reflect brain connections and activity. Functional networks, however, examine the functional relationships between regions of the brain. These networks can be established using the functional MRI imaging modality (fMRI). Connections and correlations between activated regions are used to establish adjacency between nodes in a functional network. Essentially, regions that often activate together are considered to be adjacent.

Biswal et al. [2] was one of the original studies to utilize fMRI images together with graph theoretical analysis to examine the functional network of the human brain. The study constructed a 90-node undirected graph for analysis [2]. Subsequent studies examined certain hub regions, chosen based on assumptions about brain networks, to study functional connectivity [12]. Recent studies of fMRI data have shown altered brain functional connectivity in patients with AD. A study performed using fMRI in 2010, Sanz-Arigita et al. [11], compared a group of patients suffering from mild AD to a control group of healthy patients, with those suffering from AD showing significant increases in characteristic path length.

While all the above mentioned studies utilized fMRI imaging, studies have also been conducted using MEG as the primary data source. Previous studies have indicated decreasing Fiedler value and interregional connectivity in those afflicted with Alzheimer's Disease. In particular, the study conducted by De Haan [5] showed decreases in connectivity and robustness in the functional brain networks of patients suffering from Alzheimer's using MEG as the primary data source to establish graph networks. In fact, this study concluded significant network breakdown and a loss in network robustness in patients with AD.

Meanwhile, assortativity has been used in conjunction with structural MRI results as a diagnostic marker in distinguishing healthy individuals from those suffering from schizophrenia. People with schizophrenia showed longer distances between highly connected regions, causing the assortativity of their brain networks to differ from those of healthy people [3].

Our study focuses on the use of structural MRI as the basis for network creation, and, as such, recent studies using this modality are of particular relevance. He et al., [8] conducted in 2008, examined the differences in brain structure between healthy elderly individuals of mean age 75.93, ranging from 60 to 94, and early-stage AD patients of mean age 76.65, ranging from 62 to 96. This study examined cortical thickness (CT) measurements of each brain region, using partial correlations between CT measurements to determine which regions are physically connected. To clean the raw CT data, this study controlled for age and gender while controlling each region for the cortical thickness of other regions. CT partial correlations were used to create unweighted/binary, undirected graphs. The study utilized the small world measures of characteristic path length and clustering coefficient along with nodal centrality to quantify network connectivity. Increases in both characteristic path length and clustering coefficient were reported in the AD group over the healthy control group. In addition, in the healthy group 11 regions had betweeness centrality values significantly elevated from the network average, most of which were brain regions associated with high level functions. In the AD group however, between centrality values for these high level regions were decreased, with regions associated with more basic level functions exhibiting elevated values. Since elevated betweeness centrality indicates an elevated number of effective communication channels running through a region, these results indicate that hub regions for the healthy group tend to be regions associated with higher level functions, whereas the hub regions for the AD group are associated with lower level brain functions.

Another study utilizing structural MRI, Yao et al. 2010, examined changes in the structural networks between a group of 98 healthy controls, 113 MCI subjects, and 91 AD subjects [13]. All subjects were age matched, i.e. no significant difference in age between groups. Instead of cortical thicknesses, this study examined regional cortical volumes which were controlled for age, gender, and total gray matter volume. Two regions were considered to be connected if the correlation between their cortical volume values exceeded a sparsity threshold. Once again, this study used unweighted, undirected network models. The resulting networks were analyzed using the characteristic path length and clustering coefficient. Both the MCI and AD groups exhibited increases in clustering coefficient and characterstic path length with the AD group experiencing the greatest elevation in both metrics. This study is of particular interest to us as it also utilized the Alzheimer's Disease Neuroimaging Initiative (ADNI) database.

3 Data and Methods

This section discusses the data used in our investigation as well as our methods to create networks from raw data. Section 3.1 gives background on the data used. Section 3.2 discusses our process for statiscally cleaning the raw cortical thickness data available from the ADNI database. Finally, Section 3.3 discusses our methods to utilize the statiscally cleaned data to create network models to reflect the physical structure of the brain.

3.1 Data

In our investigation we analyze *cortical thickness* measurements on human subjects from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. This dataset is publicly available and was approved by the Institutional Review Board at USNA. We use the estimates of cortical thicknesses for 68 brain regions determined by Freesurfer, a set of tools created by the Athinoula A. Martinos Center for Biomedical Imaging at Harvard University. We define the nodes in our network as the 68 regions for which cortical thickness measurements are available.

Subjects in our study are divided into four categories based on their diagnosis: normal healthy, subjects with MCI, subjects with AD, and subjects who began the study with MCI but progressed to have AD within three years of their initial visit (MCI-AD group). Subjects in each of the first three categories retained the same diagnosis for at least three years after their initial visit. Subjects were excluded from our investigation if their final recorded visit was not at least 36 months after their initial visit or if their diagnosis changed within 36 months of their initial visit (with the exception of MCI to AD). We required a 36 month stable diagnosis to ensure that data collected from subjects was truly reflective of the physical connectivity of the brain for a given group.

The study includes 126 normal healthy subjects who ranged in age from 66 to 97 (mean 81.8, sd 4.84), with a male/female distribution of 63:63. The 103 MCI subjects ranged in age from 62 to 95 (mean 80.8, sd 7.92), with a male/female distribution of 66:37. The 105 AD subjects ranged in age from 64 to 98 (mean 80.9, sd 7.71), with a male/female distribution of 48:57. The 108 subjects included in the MCI-AD group ranged in age from 62 to 95 (mean 80.5, sd 6.92), with a male/female distribution of 61:47. We excluded 86 subjects based on the 36 month stable diagnosis requirement, 48 male: 38 female.

During our analysis, three pairs of symmetric regions (left and right lobe counterparts) exhibited significantly lower degrees than the 62 other regions meaning that these six regions had significantly fewer edges or connections in the networks we created for the normal group. This phenomenon significantly skewed the graph measures we calculated for the normal diagnostic group. Further, these six regions are known to have measurement errors in the ADNI dataset. The fact that they are symmetric pairs further implies that their low degree is the result of measurement error. In response, we exclude these regions from our analysis and use the 62 remaining brains regions as the nodes in our networks. The excluded regions are the Left and Right Caudal Anterior Cingulate, Left and Right Rostral Anterior Cingulate, and the Left and Right Parahippocampal.

3.2 Controlling demographics bias

In our data, cortial thickness correlates with demographical variables such as gender, age, and even education level. As we wish to use the correlations between cortical thickness at various regions without the bias of these demographical variables, we use linear regression to remove the effect of subject age, gender, and education level on cortical thickness. We choose this model after analyzing several regressions comprised of different combinations of individual terms and interactions of the above demographic variables. A linear regression with individual terms for age, gender, education level, and diagnostic group. proved to be the simplest regression that explained the cortical thickness variance. The results of our investigation can be found in Appendix B.

3.3 Network Creation

We use a variety of methods to create our structural networks in an effort to compare methods and determine which procedures work best. These methods employ the same general progression, yet each step has several interchangable options which create diversity between the different methods we use. The steps involved in the network creation process are as follows:

1. Calculate full or partial correlations between statistically cleaned CT variables.

   Partial correlations seek to eliminate the effect of thicknesses from other regions on the correlations between the two regions being considered while full correlations do not. Following the stastical cleaning, controlled cortical thickness variables were used to determine which regions were structurally connected and therefore adjacent in our networks. Either partial or full correlations were taken between CT variables for each group and regions between which there was a significant correlation were established as adjacent in the network for that group. We implemented methods for both partial and full correlations. Full correlations were calculated by taking the Pearson correlation between the residual CT variables from the linear regression discussed above. Partial correlations were calculated by first controlling for the impact of the cortical thickness of all the other regions on the two regions being examined using a linear regression, then taking the pearson correlation between the controlled CT variables. More precisely, we used the following steps to calculate partial correlations:

   (a) For each (i, j)
   Solve the linear regression, i.e. find β_i^* that solves:

- min $\|c^i$-$(\beta_i^*)^T \cdot z^i\|_2$
- where c^i = vector of region i (for each subject)
- and z^i = all other regions (except j)

(b) Repeat with c^j and z^j to find β_j^*

(c) Find the residuals, i.e.,
$\hat{c}^i = c^i$ - $(\beta_i^*)^T \cdot z^i$
$\hat{c}^j = c^j$ - $(\beta_j^*)^T \cdot z^j$

(d) Take the correlation between $\hat{c}^i$ and $\hat{c}^j$

2. Choose whether to use only positive values, only negative values, or absolute values for the magnitudes of the correlations between regions.

   These correlation values are used in the sparsity approach (discussed below) and in weighting the edges in the network. We implemented methods for all three correlation types.

3. Determine which edges to include in the networks for each group. The two methods we used were:

   (a) Employ only false detection rate (FDR)

   The FDR method is designed to prevent the rate of inclusion of edges which falsely represent a structural connection (i.e. there is not a structural connection present) from exceeding a given threshold [1]. Pairs of nodes which have a significant partial correlation between controlled cortical thickness variables are considered adjacent and therefore an edge is included in the network between the two nodes. A partial correlation is said to be significant if:

   $$p_i \leq q \cdot \frac{i}{n \cdot (n-1)}$$

   Where p_i is the i-th smallest p-value from the correlations, q is the allowed error rate, and n is the number of nodes.

   (b) Employ sparsity thresholding in addition to FDR

   Sparsity thresholding is a method of normalizing the size of graphs across diagnostic groups by limiting the number of edges contained in the graphs. For many of the network creation combinations, one diagnostic group had significantly less edges in its network than the other groups, which resulted in scewed graph measures. Implementing a sparsity threshold ensures that the graphs for all four diagnostic groups have the same number of edges, allowing changes in network structure to be more easily identified by graph measures.

   This method first utilizes the FDR method mentioned above, then further restricts the number of edges included in the networks to a given threshold. This approach requires a predetermined sparsity level which is expressed as a percentage. Given that Graph G_n has the fewest edges, k, of any graph across the four diagnostic groups, the sparsity level, s, establishes the number of edges, m, included in the graphs for each of the diagnostic groups. That is, $s\%$ of k is the maximum number of edges, m. For each diagnostic group, the partial correlations between each pair of regions are ranked according to magnitude and the top m pairs of regions are considered adjacent and an edge is included in the network between their corresponding nodes.

Several of the network creation methods we implemented using sparsity thresholding resulted in unconnected graphs for one or more of the different groups. These unconnected networks drastically skewed our results when computing connectivity measures. In response, we implemented a breadth first search algorithm which examined unconnected networks and found the largest connected sub-component of said networks. We then used this largest sub-component in place of the larger unconnected network when computing connectivity measures. This approach is consistent with previous studies using sparsity thresholding [8, 13]. As a result of using the largest connected component rather than the unconnected full graph, the actual number of edges that appear in the network might be less than the threshold mentioned above.

In our investigation we applied sparsity levels ranging from 100% to 50% in 10% increments. Using sparsity levels less than 50% resulted in graphs which had too few edges for their connectivity to be accurately reflected by the measures used in this study.

These methods were also identically implemented using full correlations in addition to partial correlations as mentioned in the explanations.

4. Choose whether to create binary edges or use correlation values to weight the edges.

   (a) Binary Edges

   Step 3 determines which edges to include in the network. In binary networks, these edges are given identical weights of 1. If a potential edge between two nodes is not included in the network, it is given a weight of 0. Using binary networks was the more common approach in previous studies. As a result, we created binary networks in an effort to reproduce results from these studies.

   (b) Correlation Weighted Edges

   Weighted networks assign edges values between 0 and 1. We utilized correlation magnitudes as a base weight for edges included in our weighted networks. Potential edges between two nodes which were not included in the network were assigned weights of 0.

5. Choose whether or not to utilize physical parameters to scale edge weights. If scaling, decide which parameters to use and how to apply them.

   We created networks utilizing both types of edge weighting with and without scaling. Our scaling method utilized the CT measurements of adjacent regions to scale both binary edge weights and correlation based edge weights. We scaled these edge weights by the product of the average cortical thicknesses of adjacent regions (i.e. the nodes or regions which the edge connects) for each group. We scaled these average CT values to between 0 and 1 before using them to scale the edge weights. Incorporating CT measurements in the edge weights attempts to account for the impact of thinning cortical regions on the overall connectivity and effectiveness of the brain structural network.

In order to efficiently implement the large variety of methods resulting from combinations of the above choices we utilized modular coding. This means that we created functions and triggers for each of the choices listed above which can be turned off and on from a master run file. Utilizing this technique allowed us to create run files for each of the combinations we tested, simply activating and deactivating flags in the run file rather than changing the source code itself.

4 Results and Analysis

4.1 Quantifying Connectivity

We utilize our global connectivity measures of Fiedler value, normalized Fiedler value, and assortativity, in addition to the more local measures of characteristic path length, and clustering coefficient to quantify the connectivity of the networks we created. This study tests the ability of these measures to quantify changes in brain structural connectivity and distinguish between diagnostic groups. We use a variety of measures to evaluate how useful different measures are in distinguishing between diagnostic categories when paired with certain network creation methods. Our experiments provide evidence that certain measures are better at distinguishing between certain diagnostic groups but less useful in comparisons between other pairs of groups.

4.2 Significance Testing

We perform permutation testing on the results from each network creation method to verify that differences in connectivity measures between groups were statistically significant. Essentially we are testing to determine whether the between group differences in a given measure are in fact significant. Prior to our test, we computed the differences between all measures across diagnostic groups (i.e. Fiedler value for N v. MCI, N v. MCIAD, etc. for all group combinations and all measures) to use a baseline for comparison during the permutation test. Our permutation test consists of 10,000 trials in which we randomly permuted the group assignments of the individuals in the data set. We encountered a practical bottleneck in implementing our permutation testing as the regressions taken when calculating partial correlations led to lengthy run times. We parallelized our test with twenty runs each containing 500 permutations per run. In this instance, one permutation is a random permutation of each individauls' diagnostic group. We used a different seed for the random number generator for each run to prevent correlations between permutations. Once the group assignments were permuted, we created networks for the new, randomly assigned, groups and calculated connectivity measures for these networks. We compared the differences in measures between diagnostic groups to the baseline differences between networks for the original diagnostic groups. If the differences for the randomly permuted results exceded the baseline differences, we incremented a corresponding counter variable. We calculated significance p-values for all diagnostic group comparisons by dividing the corresponding counter variables by 10,000.

4.3 Results

This section contains a discussion of our with relevant computations. We report all computations in Appendix (A).

The following tables represent the results for our network creation methods which enable us to most effectively distinguish between diagnostic groups. We create the corresponding networks by using absolute values of Pearson correlations between regions with CT variables controlled for age, gender, and education level. We use the sparsity thresholding protocol in addition to false detection rate to determine which edges to include in our networks. The sparsity thresholds we employ in these results are 100%, 90%, 80%, and 70% in order of apperance. We weight these edges using the corresponding absolute values of the Pearson correlations between regions. Finally, we do not employ our CT scaling protocol to scale the correlation weighted edges. This method of network creation yields networks which, when analyzed using our connectivity measures of assortativity and characteristic, most effectively differentiate between diagnostic groups. The consistent trends present in these two measures across a variety of sparsity levels indicates that this network creation protocol is robust to changes in network size and network density (i.e. the number of edges in a network per number of nodes). Further, employing the sparsity protocol allows us to account for differences in network size (the number of edges in the graph) between diagnostic groups. When not accounted for, these size disparities can impact the non-normalized connectivity measures.

Results using a 100% sparsity threshold

Population	Average Weight	Num. Edges
Normal	0.270117	1580
MCI	0.261510	1580
MCIAD	0.250476	1580
AD	0.239598	1580

Table 1: abs05nopartmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	6.37	0.778	467362.3	0.90	3.51
MCI	4.47	0.757	435995.9	0.89	3.63
MCI-AD	3.50	0.770	410051.8	0.90	3.98
AD	6.17	0.797	364489.8	0.88	3.97

Table 2: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2345	0.1238	0.4692	0.3514	0.2683	0.152
Norm. Fiedler	0.245	0.3863	0.303	0.3477	0.1196	0.2195
Assortativity	0.1549	0.0297	0.0003	0.2039	0.0106	0.0719
Clustering coefficient	0.2248	0.2554	0.1365	0.0862	0.376	0.048
Char. path length	0.078	0.0	0.0	0.0001	0.0002	0.4648

Table 3: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Results using a 90% sparsity threshold

Population	Average Weight	Num. Edges
Normal	0.241290	1422
MCI	0.234607	1422
MCIAD	0.226228	1422
AD	0.215388	1422

Table 4: abs05nopartmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.93	0.722	357419.4	0.87	3.69
MCI	2.47	0.660	335327.8	0.85	3.87
MCI-AD	2.05	0.691	316484.1	0.86	4.25
AD	4.71	0.731	276823.0	0.84	4.15

Table 5: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0999	0.0628	0.4523	0.4044	0.1321	0.0904
Norm. Fiedler	0.0721	0.218	0.4277	0.2339	0.0584	0.1807
Assortativity	0.2167	0.0699	0.0016	0.2567	0.0186	0.0809
Clustering coefficient	0.1798	0.4629	0.0312	0.2073	0.1889	0.045
Char. path length	0.0358	0.0001	0.0005	0.0013	0.0117	0.1861

Table 6: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Results using an 80% sparsity threshold

Population	Average Weight	Num. Edges
Normal	0.211939	1264
MCI	0.209328	1264
MCIAD	0.200833	1264
AD	0.191252	1264

Table 7: abs05nopartmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.27	0.648	266840.2	0.83	3.93
MCI	1.22	0.573	252509.4	0.81	4.10
MCI-AD	1.07	0.632	235713.6	0.83	4.50
AD	2.44	0.656	205609.8	0.81	4.45

Table 8: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2101	0.1726	0.4439	0.4422	0.1848	0.1551
Norm. Fiedler	0.0821	0.364	0.4466	0.1372	0.0711	0.3222
Assortativity	0.2704	0.0869	0.0028	0.2367	0.0226	0.0975
Clustering coefficient	0.1427	0.5284	0.0935	0.1351	0.4218	0.0926
Char. path length	0.0983	0.0025	0.0039	0.0117	0.0194	0.373

Table 9: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Results using a 70% sparsity threshold

Population	Average Weight	Num. Edges
Normal	0.184052	1106
MCI	0.183910	1106
MCIAD	0.175122	1106
AD	0.168388	1106

Table 10: abs05nopartmg.st4

GROUP	FIEDLER	NORM. FIEDLER	ASSORT.	CC	L_p
N	1.17	0.444	197504.4	0.81	4.26
MCI	0.61	0.508	184463.8	0.79	4.42
MCI-AD	0.56	0.581	168569.8	0.80	4.81
AD	1.26	0.593	149812.8	0.78	4.71

Table 11: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

METRIC	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2356	0.211	0.4573	0.4648	0.2062	0.1913
Norm. Fiedler	0.1734	0.0421	0.0357	0.1402	0.1142	0.4274
Assortativity	0.2372	0.0448	0.0019	0.1821	0.0266	0.1412
Clustering coefficient	0.2157	0.4553	0.1159	0.2591	0.3523	0.147
Char. path length	0.1913	0.0136	0.0257	0.0476	0.0858	0.3228

Table 12: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Tables (2, 5, 8, and 11) show that for all sparsity levels, assortativity is monotonically decreasing as disease severity increases. The significance testing in Tables (3, 6, 9, and 12) indicates that this pattern is not statistically significant in N vs. MCI and MCI vs. MCIAD for all sparsity levels, however, assortativity is effective in distinguishing between diagnostic groups as disease severity increases, i.e. MCI vs. AD and weakly significant for MCIAD vs. AD. This decreasing trend in assortativity indicates that as disease severity increases, the strength of the connections decreases between regions of the brain which are connected to many other regions. Further, in Tables (2, 5, 8, and 11), characteristic path length exhibits an increasing trend as disease severity increases. Tables (3, 6, 9, and 12) show that this trend is statistically significant for all diagnostic group comparisons except the MCIAD vs. AD comparison. This increasing trend for Characterstic Path Length tracks with the Yao 2010 [13] study using data from the same database, i.e. the ADNI database. This trend indicates that communication must travel further on average between regions as the severity of disease increases.

Our other connectivity measures of Fielder value, normalized Fiedler value, and clustering coefficient did not effectively differentiate between diagnostic groups when paired with this network creation method. As seen in Tables (3, 6, 9, and 12) these measures occasionally produced statistically significant differences between diagnostic groups, however, this significance was not present across all sparsity levels. For instance, as seen in Tables (6 and 9), normalized Fiedler value produces statistically significant differences between the normal and MCI groups, and the MCI and the AD groups at 80 and 90% sparsity thresholds. These between group distinctions, however, are not statistically significant at the other two sparsity thresholds, as shown in Tables (3 and 12). Further, Tables (2, 5, 8, and 11) show that these measures did not exhibit consistent trends with the increase of disease severity.

The above results support analyzing the characteristic path length and assortativity of networks created using the above mentioned protocol as the most effective combination for identifying disease severity. This finding will be utilized in future research beyond the Trident Project in the effort to develop an early diagnosis tool for Alzheimer's disease.

5 Future Directions

This section addresses areas for further investigation utilizing the results from this project as a starting point for future research.

5.1 Implement Optimization

One of the major areas of investigation that is still relatively unexplored is the concept of utilizing an optimal brain network as a point for comparison between the different groups of subjects. We plan to continue work beyond the scope of the Trident Scholar project to implement a method for maximizing the efficiency and effectiveness of a model brain structural network. This optimization involves maximizing one of our connectivity measures while enforcing certain restrictions on the structure of the model, e.g. establishing maximums for how many other regions with which each region can be directly connected. Establishing an "optimal network" will create another mode of comparison between the networks of healthy and diseased individuals by determining how close they are to the optimal network.

5.2 Individualized Networks

Our current work involves creating structural network models for groups of people. This approach, however, has severe limitations in its use as a diagnosis tool for individuals. For this reason, we will work to implement methods for creating network models for individuals, thereby making an important breakthrough in the effort to develop tools and methods to diagnose and combat Alzheimer's Disease. We hope to utilize the methods we have established and innovate new ways to apply them in creating networks for individuals. This is a goal which we will work towards throughout the summer as it is a very intricate problem which requires work beyond the time frame of the Trident Scholar Project.

References

[1] Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 289–300, 1995.

[2] B. Biswal, F. Zerrin Yetkin, V.M. Haughton, and J.S. Hyde. Functional connectivity in the motor cortex of resting human brain using echo-planar MRI. *Magnetic resonance in medicine*, 34(4):537–541, 1995.

[3] E. Bullmore and O. Sporns. Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature Reviews Neuroscience*, 10(3):186–198, 2009.

[4] F.R.K. Chung. *Spectral graph theory*, volume 92. Amer Mathematical Society, 1997.

[5] W. de Haan, W.M. van der Flier, H. Wang, P.F.A. Van Mieghem, P. Scheltens, and C.J. Stam. Disruption of functional brain networks in Alzheimer's disease: What can we learn from graph spectral analysis of resting-state magnetoencephalography? *Brain Connectivity*, 2(2):45–55, 2012.

[6] Miroslav Fiedler. Algebraic connectivity of graphs. *Czechoslovak Math. J.*, 23(98):298–305, 1973.

[7] Anders M Fjell and Kristine B Walhovd. New tools for the study of Alzheimers disease what are biomarkers and morphometric markers teaching us? *The Neuroscientist*, 17(5):592–605, 2011.

[8] Y. He, Z. Chen, and A. Evans. Structural insights into aberrant topological patterns of large-scale cortical networks in alzheimer's disease. *The Journal of neuroscience*, 28(18):4756–4766, 2008.

[9] Roger A. Horn and Charles R. Johnson. *Topics in matrix analysis*. Cambridge University Press, Cambridge, 1985. 1999 reprint.

[10] M. Randić. Characterization of molecular branching. *Journal of the American Chemical Society*, 97(23):6609–6615, 1975.

[11] E.J. Sanz-Arigita, M.M. Schoonheim, J.S. Damoiseaux, S.A.R.B. Rombouts, E. Maris, F. Barkhof, P. Scheltens, and C.J. Stam. Loss of small-worldnetworks in Alzheimer's disease: graph analysis of FMRI resting-state functional connectivity. *PLoS One*, 5(11):e13788, 2010.

[12] T. Xie and Y. He. Mapping the Alzheimers brain with connectomics. *Frontiers in Psychiatry*, 2:77, 2012.

[13] Zhijun Yao, Yuanchao Zhang, Lei Lin, Yuan Zhou, Cunlu Xu, Tianzi Jiang, et al. Abnormal cortical networks in mild cognitive impairment and Alzheimer's disease. *PLoS computational biology*, 6(11):e1001006, 2010.

A Graph Measure Results

The appendix contains a full listing of the results for all of the different methods we utilized.

A.1 Absolute correlations

Population	Average Weight	Num. Edges
Normal	0.021916	117
MCI	0.036204	214
MCIAD	0.036608	238
AD	0.039149	245

Table 13: abs05mg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	409.8	0.15	9.97
MCI	0.21	0.295	1637.6	0.23	7.14
MCI-AD	0.18	0.205	2786.4	0.32	7.59
AD	0.12	0.217	2663.9	0.25	7.79

Table 14: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.218	0.2144	0.4626	0.464	0.2618	0.2673
Norm. Fiedler	0.0996	0.2809	0.2781	0.2618	0.2687	0.4977
Assortativity	0.4304	0.109	0.1623	0.1402	0.2044	0.4008
Clustering coefficient	0.5684	0.0942	0.3865	0.0814	0.344	0.1702
Char. path length	0.3124	0.3324	0.4084	0.4812	0.3764	0.3943

Table 15: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 16: abs05mg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 17: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 18: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 19: abs05mg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 20: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 21: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 22: abs05mg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 23: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 24: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 25: abs05mg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 26: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 27: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 28: abs05mg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 29: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 30: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.021592	116
MCI	0.024442	117
MCIAD	0.024963	115
AD	0.026632	114

Table 31: abs05mg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.077	399.3	0.15	10.03
MCI	0.08	0.175	394.3	0.18	9.56
MCI-AD	0.02	0.034	525.7	0.25	12.68
AD	0.08	0.204	441.2	0.20	9.69

Table 32: Graph metrics: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1196	0.3291	0.1367	0.0477	0.4691	0.0577
Norm. Fiedler	0.009	0.2111	0.0016	0.0008	0.2781	0.0001
Assortativity	0.2827	0.2687	0.5551	0.1567	0.3541	0.2496
Clustering coefficient	0.6591	0.1724	0.538	0.0888	0.3733	0.1583
Char. path length	0.3052	0.0021	0.3651	0.001	0.436	0.0016

Table 33: Permutation testing: Absolute values, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.304844	1756
MCI	0.261510	1580
MCIAD	0.280603	1786
AD	0.278119	1822

Table 34: abs05nopartmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.35	0.883	634838.6	0.94	3.31
MCI	4.47	0.757	435995.9	0.89	3.63
MCI-AD	6.75	0.880	550385.1	0.96	3.74
AD	9.13	0.916	543006.4	0.97	3.66

Table 35: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2069	0.5021	0.1308	0.2145	0.0531	0.1708
Norm. Fiedler	0.0184	0.6143	0.1144	0.0131	0.0035	0.2116
Assortativity	0.0118	0.1374	0.1357	0.0614	0.0717	0.471
Clustering coefficient	0.0269	0.0933	0.0409	0.0064	0.0034	0.3398
Char. path length	0.0002	0.0	0.0	0.0545	0.2958	0.1266

Table 36: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.270117	1580
MCI	0.261510	1580
MCIAD	0.250476	1580
AD	0.239598	1580

Table 37: abs05nopartmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	6.37	0.778	467362.3	0.90	3.51
MCI	4.47	0.757	435995.9	0.89	3.63
MCI-AD	3.50	0.770	410051.8	0.90	3.98
AD	6.17	0.797	364489.8	0.88	3.97

Table 38: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2345	0.1238	0.4692	0.3514	0.2683	0.152
Norm. Fiedler	0.245	0.3863	0.303	0.3477	0.1196	0.2195
Assortativity	0.1549	0.0297	0.0003	0.2039	0.0106	0.0719
Clustering coefficient	0.2248	0.2554	0.1365	0.0862	0.376	0.048
Char. path length	0.078	0.0	0.0	0.0001	0.0002	0.4648

Table 39: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.241290	1422
MCI	0.234607	1422
MCIAD	0.226228	1422
AD	0.215388	1422

Table 40: abs05nopartmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.93	0.722	357419.4	0.87	3.69
MCI	2.47	0.660	335327.8	0.85	3.87
MCI-AD	2.05	0.691	316484.1	0.86	4.25
AD	4.71	0.731	276823.0	0.84	4.15

Table 41: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0999	0.0628	0.4523	0.4044	0.1321	0.0904
Norm. Fiedler	0.0721	0.218	0.4277	0.2339	0.0584	0.1807
Assortativity	0.2167	0.0699	0.0016	0.2567	0.0186	0.0809
Clustering coefficient	0.1798	0.4629	0.0312	0.2073	0.1889	0.045
Char. path length	0.0358	0.0001	0.0005	0.0013	0.0117	0.1861

Table 42: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.211939	1264
MCI	0.209328	1264
MCIAD	0.200833	1264
AD	0.191252	1264

Table 43: abs05nopartmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.27	0.648	266840.2	0.83	3.93
MCI	1.22	0.573	252509.4	0.81	4.10
MCI-AD	1.07	0.632	235713.6	0.83	4.50
AD	2.44	0.656	205609.8	0.81	4.45

Table 44: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2101	0.1726	0.4439	0.4422	0.1848	0.1551
Norm. Fiedler	0.0821	0.364	0.4466	0.1372	0.0711	0.3222
Assortativity	0.2704	0.0869	0.0028	0.2367	0.0226	0.0975
Clustering coefficient	0.1427	0.5284	0.0935	0.1351	0.4218	0.0926
Char. path length	0.0983	0.0025	0.0039	0.0117	0.0194	0.373

Table 45: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.184052	1106
MCI	0.183910	1106
MCIAD	0.175122	1106
AD	0.168388	1106

Table 46: abs05nopartmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.17	0.444	197504.4	0.81	4.26
MCI	0.61	0.508	184463.8	0.79	4.42
MCI-AD	0.56	0.581	168569.8	0.80	4.81
AD	1.26	0.593	149812.8	0.78	4.71

Table 47: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2356	0.211	0.4573	0.4648	0.2062	0.1913
Norm. Fiedler	0.1734	0.0421	0.0357	0.1402	0.1142	0.4274
Assortativity	0.2372	0.0448	0.0019	0.1821	0.0266	0.1412
Clustering coefficient	0.2157	0.4553	0.1159	0.2591	0.3523	0.147
Char. path length	0.1913	0.0136	0.0257	0.0476	0.0858	0.3228

Table 48: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.157050	948
MCI	0.157543	948
MCIAD	0.150879	948
AD	0.144559	948

Table 49: abs05nopartmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.41	0.264	138583.6	0.76	4.63
MCI	0.39	0.439	125310.1	0.73	4.72
MCI-AD	0.28	0.546	117546.6	0.75	5.21
AD	1.06	0.534	102407.9	0.75	5.01

Table 50: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4561	0.3525	0.0935	0.3816	0.0845	0.0638
Norm. Fiedler	0.0687	0.021	0.0243	0.125	0.1535	0.4428
Assortativity	0.1444	0.0426	0.0014	0.2662	0.0351	0.1086
Clustering coefficient	0.1996	0.4738	0.4091	0.2201	0.2722	0.4392
Char. path length	0.3365	0.0323	0.095	0.0666	0.1768	0.2524

Table 51: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.143972	790
MCI	0.131251	790
MCIAD	0.126918	790
AD	0.120099	790

Table 52: abs05nopartmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.31	0.460	96446.2	0.78	5.02
MCI	0.31	0.357	80592.2	0.69	5.20
MCI-AD	0.06	0.339	76430.8	0.70	6.39
AD	0.45	0.467	64946.4	0.72	5.38

Table 53: Graph metrics: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.456	0.1225	0.2649	0.146	0.2439	0.0723
Norm. Fiedler	0.1696	0.1354	0.4926	0.4249	0.1667	0.1318
Assortativity	0.0303	0.007	0.0	0.3076	0.0323	0.0821
Clustering coefficient	0.0028	0.0076	0.0237	0.382	0.2277	0.3279
Char. path length	0.3129	0.0023	0.1856	0.0077	0.3426	0.0155

Table 54: Permutation testing: Absolute values, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.913632	1756
MCI	0.822060	1580
MCIAD	0.929240	1786
AD	0.947971	1822

Table 55: abs05nopartnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	40.68	0.888	5730156.0	0.95	1.07
MCI	21.61	0.805	4354002.0	0.89	1.16
MCI-AD	40.01	0.865	6004728.0	0.96	1.06
AD	43.80	0.928	6327146.0	0.97	1.04

Table 56: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1191	0.6153	0.2364	0.0843	0.0451	0.3571
Norm. Fiedler	0.1012	0.4412	0.1002	0.1383	0.0134	0.1023
Assortativity	0.0251	0.1505	0.0397	0.0087	0.0033	0.2514
Clustering coefficient	0.0253	0.1298	0.046	0.0072	0.0034	0.2982
Char. path length	0.0127	0.1374	0.0339	0.0056	0.0022	0.2333

Table 57: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.822060	1580
MCI	0.822060	1580
MCIAD	0.822060	1580
AD	0.822060	1580

Table 58: abs05nopartnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	20.65	0.797	4389207.0	0.90	1.16
MCI	21.61	0.805	4354002.0	0.89	1.16
MCI-AD	20.10	0.738	4369511.0	0.90	1.16
AD	21.75	0.819	4322283.0	0.89	1.16

Table 59: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4348	0.4866	0.4315	0.4255	0.4999	0.4261
Norm. Fiedler	0.4549	0.049	0.3152	0.0394	0.3513	0.018
Assortativity	0.2518	0.3529	0.0996	0.3805	0.2787	0.1815
Clustering coefficient	0.1562	0.469	0.0791	0.1424	0.3614	0.0798
Char. path length	0.0	0.0	0.0	0.0	0.0	0.0

Table 60: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.739854	1422
MCI	0.739854	1422
MCIAD	0.739854	1422
AD	0.739854	1422

Table 61: abs05nopartnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	12.75	0.737	3405188.0	0.87	1.25
MCI	12.35	0.734	3373008.0	0.86	1.25
MCI-AD	12.08	0.654	3348934.0	0.86	1.25
AD	12.77	0.763	3290921.0	0.84	1.25

Table 62: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4912	0.4717	0.4864	0.4724	0.4823	0.468
Norm. Fiedler	0.4436	0.0366	0.3153	0.048	0.2696	0.0155
Assortativity	0.3201	0.1955	0.0377	0.3504	0.1021	0.1824
Clustering coefficient	0.1473	0.3323	0.0228	0.269	0.185	0.067
Char. path length	0.0	0.0	0.0	0.0	0.0	0.0

Table 63: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.657648	1264
MCI	0.657648	1264
MCIAD	0.657648	1264
AD	0.657648	1264

Table 64: abs05nopartnowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.82	0.679	2604635.0	0.84	1.34
MCI	7.14	0.638	2521603.0	0.82	1.33
MCI-AD	6.58	0.594	2516391.0	0.83	1.34
AD	9.67	0.699	2452084.0	0.81	1.33

Table 65: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.3008	0.356	0.1547	0.4485	0.3202	0.2639
Norm. Fiedler	0.2203	0.075	0.3862	0.2234	0.1523	0.0528
Assortativity	0.1174	0.0978	0.0093	0.468	0.1517	0.1722
Clustering coefficient	0.129	0.4223	0.0722	0.178	0.3933	0.1109
Char. path length	0.4262	0.2779	0.2578	0.2312	0.3138	0.1649

Table 66: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.575442	1106
MCI	0.575442	1106
MCIAD	0.575442	1106
AD	0.575442	1106

Table 67: abs05nopartnowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.52	0.514	1953528.0	0.81	1.45
MCI	3.87	0.517	1830997.0	0.79	1.43
MCI-AD	3.69	0.545	1818308.0	0.80	1.44
AD	7.64	0.642	1768938.0	0.78	1.42

Table 68: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2287	0.2446	0.029	0.4578	0.1316	0.1131
Norm. Fiedler	0.5111	0.3589	0.0834	0.3568	0.0869	0.1222
Assortativity	0.0296	0.0163	0.0015	0.4222	0.1649	0.2229
Clustering coefficient	0.2347	0.4031	0.1058	0.3206	0.3127	0.1656
Char. path length	0.1699	0.2099	0.1008	0.3859	0.2903	0.2256

Table 69: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.493236	948
MCI	0.493236	948
MCIAD	0.493236	948
AD	0.493236	948

Table 70: abs05nopartnowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.53	0.321	1379707.0	0.75	1.59
MCI	2.43	0.493	1256911.0	0.73	1.54
MCI-AD	1.83	0.510	1259227.0	0.75	1.54
AD	6.41	0.565	1207896.0	0.74	1.51

Table 71: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1549	0.2319	0.0019	0.3556	0.0238	0.013
Norm. Fiedler	0.1094	0.0932	0.0579	0.4337	0.2529	0.2912
Assortativity	0.0174	0.0151	0.0012	0.4888	0.1864	0.1843
Clustering coefficient	0.2269	0.4586	0.4047	0.2646	0.3111	0.4501
Char. path length	0.1246	0.1302	0.0558	0.4798	0.2671	0.2535

Table 72: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.453893	790
MCI	0.411030	790
MCIAD	0.411030	790
AD	0.411030	790

Table 73: abs05nopartnowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.71	0.482	958511.0	0.78	1.64
MCI	1.87	0.379	812979.0	0.69	1.68
MCI-AD	0.51	0.287	809591.0	0.70	1.75
AD	2.73	0.466	776531.0	0.72	1.62

Table 74: Graph metrics: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1221	0.3495	0.0378	0.0861	0.1771	0.0266
Norm. Fiedler	0.2199	0.1015	0.4233	0.2453	0.2665	0.1226
Assortativity	0.0008	0.0007	0.0001	0.4667	0.2145	0.2415
Clustering coefficient	0.0038	0.008	0.0273	0.4002	0.2315	0.3145
Char. path length	0.2602	0.0528	0.4238	0.151	0.2041	0.0332

Table 75: Permutation testing: Absolute values, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.065000	117
MCI	0.111342	214
MCIAD	0.123829	238
AD	0.131685	245

Table 76: abs05nowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3867.0	0.16	3.42
MCI	0.71	0.293	14975.0	0.23	2.41
MCI-AD	0.61	0.197	32609.0	0.33	2.49
AD	0.43	0.237	31198.0	0.25	2.38

Table 77: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1869	0.1978	0.4319	0.4724	0.2673	0.2739
Norm. Fiedler	0.0728	0.2578	0.165	0.238	0.3392	0.3831
Assortativity	0.396	0.0501	0.0772	0.0663	0.1032	0.3847
Clustering coefficient	0.5895	0.0889	0.412	0.0697	0.3462	0.1478
Char. path length	0.2234	0.2004	0.1798	0.5385	0.4191	0.4565

Table 78: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 79: abs05nowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 80: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 81: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 82: abs05nowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 83: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 84: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 85: abs05nowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 86: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 87: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 88: abs05nowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 89: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 90: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 91: abs05nowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 92: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 93: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.064444	116
MCI	0.074617	117
MCIAD	0.085059	115
AD	0.091200	114

Table 94: abs05nowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.13	0.061	3823.0	0.16	3.43
MCI	0.48	0.163	3435.0	0.18	3.02
MCI-AD	0.06	0.031	6814.0	0.26	3.91
AD	0.31	0.193	5435.0	0.20	2.88

Table 95: Graph metrics: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0017	0.3204	0.0579	0.0003	0.0877	0.0191
Norm. Fiedler	0.0057	0.294	0.0008	0.0011	0.2583	0.0003
Assortativity	0.1026	0.0152	0.1204	0.0045	0.0337	0.0693
Clustering coefficient	0.6853	0.1618	0.5616	0.069	0.3685	0.1326
Char. path length	0.0258	0.0097	0.0061	0.0006	0.2549	0.0001

Table 96: Permutation testing: Absolute values, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006915	117
MCI	0.012361	214
MCIAD	0.012499	238
AD	0.013117	245

Table 97: abs05wtmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	41.4	0.16	16.62
MCI	0.07	0.286	194.5	0.24	19.93
MCI-AD	0.06	0.211	335.3	0.33	19.28
AD	0.04	0.210	310.4	0.26	18.09

Table 98: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2313	0.2278	0.517	0.4738	0.2451	0.2488
Norm. Fiedler	0.076	0.192	0.2367	0.3041	0.2635	0.4542
Assortativity	0.4289	0.097	0.1592	0.1273	0.2055	0.3629
Clustering coefficient	0.5741	0.0968	0.3895	0.0838	0.3427	0.174
Char. path length	0.0456	0.088	0.1313	0.3172	0.2173	0.3818

Table 99: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 100: abs05wtmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 101: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 102: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 103: abs05wtmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 104: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 105: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 106: abs05wtmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 107: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 108: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 109: abs05wtmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 110: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 111: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 112: abs05wtmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 113: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 114: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.006833	116
MCI	0.009369	117
MCIAD	0.009919	115
AD	0.010353	114

Table 115: abs05wtmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.061	40.6	0.16	16.63
MCI	0.03	0.164	58.8	0.18	20.45
MCI-AD	0.01	0.033	84.7	0.26	17.74
AD	0.03	0.205	69.1	0.20	15.69

Table 116: Graph metrics: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2384	0.2148	0.3019	0.0646	0.4208	0.0901
Norm. Fiedler	0.0174	0.2352	0.0016	0.0016	0.1872	0.0001
Assortativity	0.6111	0.137	0.3692	0.1106	0.305	0.2223
Clustering coefficient	0.6797	0.1746	0.5406	0.0818	0.3545	0.1596
Char. path length	0.0652	0.2524	0.5752	0.1863	0.078	0.2964

Table 117: Permutation testing: Absolute values, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.127417	1756
MCI	0.104063	1580
MCIAD	0.130819	1786
AD	0.126105	1822

Table 118: abs05wtnopartmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.41	0.819	113377.3	0.96	8.60
MCI	1.25	0.655	70746.4	0.90	10.02
MCI-AD	2.16	0.813	121034.9	0.97	8.77
AD	3.36	0.842	112587.5	0.97	8.66

Table 119: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2167	0.4676	0.1552	0.2485	0.05	0.1588
Norm. Fiedler	0.0063	0.5231	0.2362	0.0065	0.0019	0.28
Assortativity	0.1529	0.4082	0.5201	0.1153	0.1598	0.4258
Clustering coefficient	0.0137	0.1248	0.0612	0.0048	0.0025	0.3542
Char. path length	0.0208	0.3967	0.4597	0.0391	0.0298	0.438

Table 120: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.120107	1580
MCI	0.104063	1580
MCIAD	0.123343	1580
AD	0.116365	1580

Table 121: abs05wtnopartmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.20	0.743	95758.8	0.91	8.62
MCI	1.25	0.655	70746.4	0.90	10.02
MCI-AD	1.30	0.728	101261.3	0.91	8.78
AD	2.33	0.748	87722.9	0.90	8.69

Table 122: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1821	0.1825	0.4448	0.4907	0.1553	0.1632
Norm. Fiedler	0.0223	0.3503	0.4605	0.0493	0.0214	0.3154
Assortativity	0.1626	0.4193	0.3752	0.1283	0.265	0.3042
Clustering coefficient	0.0981	0.5082	0.0369	0.1007	0.3172	0.0432
Char. path length	0.0167	0.3883	0.4393	0.0335	0.0255	0.4499

Table 123: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.112504	1422
MCI	0.098177	1422
MCIAD	0.115621	1422
AD	0.108678	1422

Table 124: abs05wtnopartmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.67	0.698	80976.1	0.88	8.67
MCI	0.78	0.561	60077.4	0.87	10.05
MCI-AD	0.82	0.664	84363.9	0.88	8.84
AD	1.86	0.690	72102.2	0.86	8.74

Table 125: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1333	0.1415	0.4041	0.4848	0.1014	0.1068
Norm. Fiedler	0.0054	0.2326	0.4323	0.0248	0.0086	0.2994
Assortativity	0.1587	0.4431	0.3357	0.1374	0.2933	0.2883
Clustering coefficient	0.0735	0.2513	0.007	0.2137	0.1762	0.0442
Char. path length	0.0146	0.3691	0.4332	0.0299	0.0224	0.4394

Table 126: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.103614	1264
MCI	0.091677	1264
MCIAD	0.106469	1264
AD	0.100179	1264

Table 127: abs05wtnopartmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.83	0.630	66600.6	0.85	8.82
MCI	0.42	0.488	49602.8	0.83	10.09
MCI-AD	0.47	0.613	67576.8	0.84	8.98
AD	1.05	0.626	57804.7	0.82	8.84

Table 128: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2346	0.2603	0.3453	0.4764	0.1476	0.1619
Norm. Fiedler	0.0147	0.372	0.4696	0.0239	0.017	0.4138
Assortativity	0.1561	0.4803	0.3014	0.1572	0.3197	0.2902
Clustering coefficient	0.0966	0.3661	0.0523	0.1708	0.3887	0.109
Char. path length	0.0184	0.3764	0.4695	0.0373	0.0249	0.4113

Table 129: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.094158	1106
MCI	0.084148	1106
MCIAD	0.096250	1106
AD	0.091361	1106

Table 130: abs05wtnopartmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.46	0.438	53857.7	0.82	9.11
MCI	0.23	0.429	39590.5	0.80	10.32
MCI-AD	0.26	0.566	51892.6	0.81	9.17
AD	0.60	0.573	45196.0	0.79	8.96

Table 131: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2669	0.2859	0.3467	0.4757	0.1698	0.1861
Norm. Fiedler	0.436	0.0495	0.0442	0.0425	0.0376	0.463
Assortativity	0.1378	0.4368	0.2552	0.1867	0.3379	0.3114
Clustering coefficient	0.2034	0.3624	0.0942	0.3166	0.3203	0.172
Char. path length	0.0262	0.4295	0.4502	0.0388	0.022	0.389

Table 132: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.084085	948
MCI	0.075486	948
MCIAD	0.085857	948
AD	0.081368	948

Table 133: abs05wtnopartmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.17	0.269	41440.7	0.77	9.48
MCI	0.16	0.373	29594.0	0.74	10.54
MCI-AD	0.15	0.527	38708.0	0.76	9.55
AD	0.51	0.521	33264.1	0.76	9.15

Table 134: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4658	0.4292	0.0844	0.4573	0.0767	0.0705
Norm. Fiedler	0.1369	0.0247	0.0263	0.0701	0.0752	0.4732
Assortativity	0.1106	0.3872	0.2008	0.1837	0.354	0.2917
Clustering coefficient	0.2082	0.4082	0.3889	0.275	0.3013	0.477
Char. path length	0.0686	0.4186	0.3766	0.0951	0.0402	0.3016

Table 135: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.080824	790
MCI	0.066005	790
MCIAD	0.074760	790
AD	0.070242	790

Table 136: abs05wtnopartmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.14	0.455	31442.8	0.79	9.71
MCI	0.14	0.298	20988.9	0.70	10.91
MCI-AD	0.03	0.329	26925.5	0.71	10.87
AD	0.23	0.457	22785.8	0.73	9.51

Table 137: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4361	0.1481	0.2335	0.1841	0.2082	0.0759
Norm. Fiedler	0.0909	0.1225	0.5125	0.3786	0.0917	0.1259
Assortativity	0.0617	0.2523	0.1016	0.1957	0.3953	0.2757
Clustering coefficient	0.0034	0.005	0.0219	0.4395	0.252	0.3019
Char. path length	0.1031	0.1132	0.4665	0.4776	0.0865	0.0916

Table 138: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.388680	1756
MCI	0.327249	1580
MCIAD	0.430533	1786
AD	0.430900	1822

Table 139: abs05wtnopartnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	11.06	0.828	1059294.6	0.96	2.78
MCI	6.63	0.732	708834.3	0.90	3.08
MCI-AD	12.41	0.795	1306274.8	0.97	2.44
AD	14.14	0.855	1317807.5	0.97	2.44

Table 140: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2656	0.3168	0.1927	0.1497	0.0825	0.3571
Norm. Fiedler	0.0543	0.3125	0.2126	0.1327	0.0148	0.1234
Assortativity	0.1606	0.211	0.1931	0.0431	0.0399	0.4774
Clustering coefficient	0.0139	0.1478	0.0641	0.0054	0.0024	0.326
Char. path length	0.1088	0.079	0.0756	0.0081	0.0067	0.4904

Table 141: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.369316	1580
MCI	0.327249	1580
MCIAD	0.403972	1580
AD	0.398994	1580

Table 142: abs05wtnopartnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	6.49	0.763	915667.9	0.92	2.78
MCI	6.63	0.732	708834.3	0.90	3.08
MCI-AD	7.46	0.697	1077178.2	0.91	2.44
AD	8.77	0.773	1038956.0	0.90	2.45

Table 143: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4603	0.371	0.2345	0.4138	0.2753	0.3524
Norm. Fiedler	0.1903	0.042	0.4274	0.1977	0.1463	0.0276
Assortativity	0.1507	0.2195	0.28	0.0446	0.0634	0.4332
Clustering coefficient	0.0753	0.3321	0.0228	0.1605	0.3005	0.065
Char. path length	0.0901	0.0607	0.0618	0.0046	0.0047	0.4932

Table 144: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.347595	1422
MCI	0.309256	1422
MCIAD	0.377817	1422
AD	0.372904	1422

Table 145: abs05wtnopartnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.12	0.715	781671.4	0.89	2.81
MCI	4.37	0.654	606029.0	0.87	3.09
MCI-AD	4.91	0.629	893691.1	0.88	2.47
AD	5.93	0.724	856077.5	0.86	2.47

Table 146: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.448	0.3807	0.2507	0.4369	0.3067	0.3665
Norm. Fiedler	0.088	0.0317	0.4454	0.2991	0.0756	0.0248
Assortativity	0.1391	0.2573	0.3337	0.0494	0.0771	0.4163
Clustering coefficient	0.0673	0.1717	0.0058	0.2831	0.1692	0.0642
Char. path length	0.086	0.0458	0.049	0.0033	0.0032	0.4931

Table 147: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.322714	1264
MCI	0.288126	1264
MCIAD	0.348192	1264
AD	0.343946	1264

Table 148: abs05wtnopartnowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.70	0.665	653503.9	0.85	2.88
MCI	2.50	0.580	498767.3	0.83	3.11
MCI-AD	2.89	0.578	721312.9	0.84	2.52
AD	4.78	0.669	688035.4	0.82	2.52

Table 149: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.3464	0.2907	0.0779	0.439	0.1632	0.2019
Norm. Fiedler	0.0766	0.0669	0.4947	0.4838	0.075	0.0663
Assortativity	0.1163	0.3122	0.4041	0.054	0.0875	0.4044
Clustering coefficient	0.091	0.2877	0.0417	0.222	0.3566	0.1293
Char. path length	0.1019	0.0329	0.0346	0.0027	0.0029	0.4989

Table 150: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.294842	1106
MCI	0.263779	1106
MCIAD	0.315517	1106
AD	0.312205	1106

Table 151: abs05wtnopartnowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.60	0.509	533318.7	0.82	3.00
MCI	1.49	0.479	396913.4	0.80	3.18
MCI-AD	1.73	0.535	558605.2	0.81	2.59
AD	3.64	0.618	534095.9	0.79	2.58

Table 152: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2741	0.2275	0.0259	0.4426	0.0836	0.1091
Norm. Fiedler	0.3179	0.3769	0.1017	0.2244	0.0684	0.1431
Assortativity	0.0896	0.4074	0.5083	0.065	0.1029	0.4099
Clustering coefficient	0.2216	0.3245	0.0855	0.3779	0.2824	0.1868
Char. path length	0.1537	0.017	0.0173	0.0027	0.0019	0.4882

Table 153: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.264172	948
MCI	0.236776	948
MCIAD	0.280263	948
AD	0.277697	948

Table 154: abs05wtnopartnowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.22	0.326	412131.3	0.77	3.15
MCI	1.03	0.451	299731.9	0.74	3.25
MCI-AD	0.95	0.497	414478.2	0.76	2.68
AD	3.11	0.548	392819.3	0.76	2.66

Table 155: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1838	0.2082	0.0026	0.4401	0.019	0.0176
Norm. Fiedler	0.1596	0.1073	0.069	0.318	0.192	0.2976
Assortativity	0.0705	0.4884	0.3934	0.0745	0.1235	0.3957
Clustering coefficient	0.2295	0.3914	0.3804	0.3219	0.3369	0.489
Char. path length	0.267	0.0106	0.0099	0.0038	0.0025	0.4569

Table 156: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.254641	790
MCI	0.207128	790
MCIAD	0.242171	790
AD	0.240314	790

Table 157: abs05wtnopartnowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.33	0.478	312157.0	0.79	3.08
MCI	0.82	0.354	213982.3	0.70	3.37
MCI-AD	0.27	0.278	285773.6	0.71	2.94
AD	1.40	0.457	272199.3	0.73	2.76

Table 158: Graph metrics: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1646	0.3974	0.0365	0.1312	0.1249	0.0301
Norm. Fiedler	0.1824	0.095	0.4097	0.2774	0.2287	0.1202
Assortativity	0.0365	0.3074	0.2296	0.103	0.1534	0.4063
Clustering coefficient	0.0038	0.0053	0.0248	0.4571	0.2576	0.29
Char. path length	0.0865	0.2996	0.1007	0.0343	0.0054	0.2326

Table 159: Permutation testing: Absolute values, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020652	117
MCI	0.037872	214
MCIAD	0.042718	238
AD	0.044135	245

Table 160: abs05wtnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	396.3	0.16	10.98
MCI	0.23	0.283	1761.5	0.24	6.96
MCI-AD	0.19	0.201	4069.3	0.33	7.24
AD	0.13	0.230	3660.3	0.26	7.04

Table 161: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1979	0.1989	0.4736	0.4824	0.2571	0.2515
Norm. Fiedler	0.059	0.1828	0.1383	0.2797	0.342	0.4265
Assortativity	0.3957	0.0372	0.0728	0.051	0.099	0.3018
Clustering coefficient	0.598	0.0937	0.4147	0.0713	0.3436	0.1523
Char. path length	0.169	0.1452	0.1454	0.5615	0.5539	0.5123

Table 162: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 163: abs05wtnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 164: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 165: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 166: abs05wtnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 167: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 168: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 169: abs05wtnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 170: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 171: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 172: abs05wtnowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 173: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 174: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 175: abs05wtnowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 176: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 177: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 178: abs05wtnowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 179: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 180: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.020511	116
MCI	0.028465	117
MCIAD	0.034291	115
AD	0.035378	114

Table 181: abs05wtnowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.048	392.8	0.16	11.00
MCI	0.17	0.153	506.2	0.18	7.89
MCI-AD	0.02	0.030	1138.2	0.26	9.96
AD	0.10	0.197	855.0	0.20	7.48

Table 182: Graph metrics: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0092	0.2145	0.1713	0.0007	0.0657	0.0351
Norm. Fiedler	0.016	0.3079	0.001	0.0026	0.1597	0.0002
Assortativity	0.7298	0.0093	0.0751	0.0052	0.0442	0.0572
Clustering coefficient	0.706	0.1626	0.5629	0.0632	0.348	0.134
Char. path length	0.1974	0.6372	0.1383	0.0422	0.2625	0.0222

Table 183: Permutation testing: Absolute values, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

A.2 Positive Correlations

Population	Average Weight	Num. Edges
Normal	0.015941	70
MCI	0.024181	131
MCIAD	0.023893	144
AD	0.024579	153

Table 184: pos05mg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.03	0.045	95.6	0.00	13.23
MCI	0.19	0.214	414.9	0.00	8.66
MCI-AD	0.06	0.127	612.6	0.00	10.01
AD	0.09	0.194	624.9	0.00	9.82

Table 185: Graph metrics: Positive correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.065	0.4871	0.3135	0.0735	0.1229	0.3369
Norm. Fiedler	0.1113	0.341	0.128	0.2215	0.4538	0.2506
Assortativity	0.3511	0.1007	0.1301	0.1793	0.2147	0.5307
Clustering coefficient	0.0	0.0	0.1775	0.0	0.1681	0.1713
Char. path length	0.2115	0.3153	0.3211	0.34	0.3252	0.5115

Table 186: Permutation testing: Positive correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.015850	67
MCI	0.018228	70
MCIAD	0.024658	61
AD	0.019656	66

Table 187: pos05mg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.02	0.028	84.8	0.00	14.27
MCI	0.04	0.080	108.7	0.00	11.83
MCI-AD	0.04	0.056	91.8	0.00	12.84
AD	0.04	0.092	86.3	0.00	12.73

Table 188: Graph metrics: Positive correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1116	0.1745	0.1839	0.3722	0.3623	0.5048
Norm. Fiedler	0.0609	0.1896	0.0243	0.2189	0.325	0.1118
Assortativity	0.318	0.5145	0.6192	0.3104	0.2462	0.4124
Clustering coefficient	0.0	0.0	0.0	0.0	0.0	0.0
Char. path length	0.2447	0.3721	0.3815	0.3515	0.3464	0.5017

Table 189: Permutation testing: Positive correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.304844	1756
MCI	0.261510	1580
MCIAD	0.280603	1786
AD	0.278119	1822

Table 190: pos05nopartmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.35	0.883	634838.6	0.94	3.31
MCI	4.47	0.757	435995.9	0.89	3.63
MCI-AD	6.75	0.880	550385.1	0.96	3.74
AD	9.13	0.916	543006.4	0.97	3.66

Table 191: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2069	0.5021	0.1308	0.2146	0.0531	0.1708
Norm. Fiedler	0.0184	0.6143	0.1144	0.0131	0.0035	0.2116
Assortativity	0.0118	0.1374	0.1357	0.0614	0.0717	0.471
Clustering coefficient	0.0269	0.0933	0.0409	0.0064	0.0034	0.3398
Char. path length	0.0002	0.0	0.0	0.0546	0.2958	0.1266

Table 192: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.270117	1580
MCI	0.261510	1580
MCIAD	0.250476	1580
AD	0.239598	1580

Table 193: pos05nopartmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.17	0.888	620122.8	0.93	3.32
MCI	5.18	0.810	384211.9	0.83	3.53
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 194: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1782	0.3584	0.2723	0.2916	0.0699	0.1719
Norm. Fiedler	0.0042	0.2836	0.233	0.0089	0.0014	0.1105
Assortativity	0.0016	0.0309	0.0154	0.0071	0.0148	0.1093
Clustering coefficient	0.0019	0.0063	0.0282	0.0007	0.0009	0.1316
Char. path length	0.0002	0.0	0.0	0.0226	0.1329	0.1803

Table 195: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.241290	1422
MCI	0.234607	1422
MCIAD	0.226228	1422
AD	0.215388	1422

Table 196: pos05nopartmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.51	0.886	621073.1	0.93	3.31
MCI	5.54	0.788	359506.0	0.82	3.63
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 197: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1967	0.3615	0.2681	0.3083	0.0817	0.1719
Norm. Fiedler	0.0021	0.2735	0.2327	0.0048	0.0009	0.1105
Assortativity	0.0014	0.0301	0.0148	0.0063	0.0143	0.1093
Clustering coefficient	0.0016	0.0063	0.0292	0.0007	0.0012	0.1316
Char. path length	0.0001	0.0	0.0	0.0309	0.1662	0.1803

Table 198: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.211939	1264
MCI	0.209328	1264
MCIAD	0.200833	1264
AD	0.191252	1264

Table 199: pos05nopartmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.86	0.886	621687.7	0.93	3.28
MCI	4.69	0.802	359069.4	0.82	3.66
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 200: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1853	0.3536	0.2749	0.3016	0.0782	0.1719
Norm. Fiedler	0.0027	0.2899	0.2253	0.0057	0.0011	0.1105
Assortativity	0.0015	0.031	0.0154	0.0067	0.0144	0.1093
Clustering coefficient	0.0017	0.0062	0.026	0.0008	0.0011	0.1316
Char. path length	0.0	0.0	0.0	0.0285	0.1457	0.1803

Table 201: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.184052	1106
MCI	0.183910	1106
MCIAD	0.175122	1106
AD	0.168388	1106

Table 202: pos05nopartmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.35	0.886	620849.6	0.93	3.32
MCI	4.91	0.787	362924.2	0.82	3.60
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 203: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1993	0.3719	0.2568	0.3069	0.0774	0.1719
Norm. Fiedler	0.0025	0.2859	0.2232	0.0056	0.0008	0.1105
Assortativity	0.0016	0.0308	0.0154	0.0062	0.0138	0.1093
Clustering coefficient	0.0019	0.0062	0.0228	0.0007	0.0011	0.1316
Char. path length	0.0001	0.0	0.0	0.0436	0.1929	0.1803

Table 204: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.157050	948
MCI	0.157543	948
MCIAD	0.150879	948
AD	0.144559	948

Table 205: pos05nopartmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.65	0.887	623899.7	0.94	3.29
MCI	5.11	0.782	356485.0	0.82	3.65
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 206: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1836	0.3549	0.2739	0.2968	0.0744	0.1719
Norm. Fiedler	0.0019	0.2877	0.2207	0.0035	0.0007	0.1105
Assortativity	0.0015	0.0309	0.015	0.0059	0.0122	0.1093
Clustering coefficient	0.0017	0.0064	0.0272	0.0006	0.0011	0.1316
Char. path length	0.0	0.0	0.0	0.0434	0.2036	0.1803

Table 207: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.143972	790
MCI	0.131251	790
MCIAD	0.126918	790
AD	0.120099	790

Table 208: pos05nopartmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	7.35	0.885	625827.1	0.94	3.31
MCI	5.35	0.784	356119.5	0.82	3.65
MCI-AD	6.46	0.873	543942.0	0.96	3.76
AD	8.79	0.898	503212.2	0.95	3.69

Table 209: Graph metrics: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2003	0.3641	0.2647	0.3132	0.0795	0.1719
Norm. Fiedler	0.0035	0.2889	0.2201	0.0067	0.0011	0.1105
Assortativity	0.0017	0.0302	0.015	0.0066	0.0136	0.1093
Clustering coefficient	0.0016	0.0064	0.0263	0.0007	0.0011	0.1316
Char. path length	0.0001	0.0	0.0	0.0367	0.1629	0.1803

Table 210: Permutation testing: Positive correlations, binary edges, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.913632	1756
MCI	0.822060	1580
MCIAD	0.929240	1786
AD	0.947971	1822

Table 211: pos05nopartnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	40.68	0.888	5730156.0	0.95	1.07
MCI	21.61	0.805	4354002.0	0.89	1.16
MCI-AD	40.01	0.865	6004728.0	0.96	1.06
AD	43.80	0.928	6327146.0	0.97	1.04

Table 212: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1191	0.6153	0.2364	0.0844	0.0451	0.3571
Norm. Fiedler	0.1012	0.4412	0.1002	0.1383	0.0135	0.1023
Assortativity	0.0251	0.1505	0.0397	0.0087	0.0033	0.2514
Clustering coefficient	0.0253	0.1298	0.046	0.0072	0.0034	0.2982
Char. path length	0.0127	0.1374	0.0339	0.0056	0.0022	0.2333

Table 213: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.822060	1580
MCI	0.822060	1580
MCIAD	0.822060	1580
AD	0.822060	1580

Table 214: pos05nopartnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	20.65	0.797	4389207.0	0.90	1.16
MCI	21.61	0.805	4354002.0	0.89	1.16
MCI-AD	20.10	0.738	4369511.0	0.90	1.16
AD	21.75	0.819	4322283.0	0.89	1.16

Table 215: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4348	0.4866	0.4315	0.4255	0.4999	0.4261
Norm. Fiedler	0.4549	0.049	0.3152	0.0394	0.3513	0.018
Assortativity	0.2518	0.3529	0.0996	0.3805	0.2787	0.1815
Clustering coefficient	0.1562	0.469	0.0791	0.1424	0.3614	0.0798
Char. path length	0.0	0.0	0.0	0.0	0.0	0.0

Table 216: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.739854	1422
MCI	0.739854	1422
MCIAD	0.739854	1422
AD	0.739854	1422

Table 217: pos05nopartnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	12.75	0.737	3405188.0	0.87	1.25
MCI	12.35	0.734	3373008.0	0.86	1.25
MCI-AD	12.08	0.654	3348934.0	0.86	1.25
AD	12.77	0.763	3290921.0	0.84	1.25

Table 218: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4912	0.4717	0.4864	0.4724	0.4823	0.468
Norm. Fiedler	0.4436	0.0366	0.3153	0.048	0.2696	0.0155
Assortativity	0.3201	0.1955	0.0377	0.3504	0.1021	0.1824
Clustering coefficient	0.1473	0.3323	0.0228	0.269	0.185	0.067
Char. path length	0.0	0.0	0.0	0.0	0.0	0.0

Table 219: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.657648	1264
MCI	0.657648	1264
MCIAD	0.657648	1264
AD	0.657648	1264

Table 220: pos05nopartnowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.82	0.679	2604635.0	0.84	1.34
MCI	7.14	0.638	2521603.0	0.82	1.33
MCI-AD	6.58	0.594	2516391.0	0.83	1.34
AD	9.67	0.699	2452084.0	0.81	1.33

Table 221: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.3008	0.356	0.1547	0.4485	0.3202	0.2639
Norm. Fiedler	0.2203	0.075	0.3862	0.2234	0.1523	0.0528
Assortativity	0.1174	0.0978	0.0093	0.468	0.1517	0.1722
Clustering coefficient	0.129	0.4223	0.0722	0.178	0.3933	0.1109
Char. path length	0.4262	0.2779	0.2578	0.2312	0.3138	0.1649

Table 222: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.575442	1106
MCI	0.575442	1106
MCIAD	0.575442	1106
AD	0.575442	1106

Table 223: pos05nopartnowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.52	0.514	1953528.0	0.81	1.45
MCI	3.87	0.517	1830997.0	0.79	1.43
MCI-AD	3.69	0.545	1818308.0	0.80	1.44
AD	7.64	0.642	1768938.0	0.78	1.42

Table 224: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2287	0.2446	0.029	0.4578	0.1316	0.1131
Norm. Fiedler	0.5111	0.3589	0.0834	0.3568	0.0869	0.1222
Assortativity	0.0296	0.0163	0.0015	0.4222	0.1649	0.2229
Clustering coefficient	0.2347	0.4031	0.1058	0.3206	0.3127	0.1656
Char. path length	0.1699	0.2099	0.1008	0.3859	0.2903	0.2256

Table 225: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.493236	948
MCI	0.493236	948
MCIAD	0.493236	948
AD	0.493236	948

Table 226: pos05nopartnowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.53	0.321	1379707.0	0.75	1.59
MCI	2.43	0.493	1256911.0	0.73	1.54
MCI-AD	1.83	0.510	1259227.0	0.75	1.54
AD	6.41	0.565	1207896.0	0.74	1.51

Table 227: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1549	0.2319	0.0019	0.3556	0.0238	0.013
Norm. Fiedler	0.1094	0.0932	0.0579	0.4337	0.2529	0.2912
Assortativity	0.0174	0.0151	0.0012	0.4888	0.1864	0.1843
Clustering coefficient	0.2269	0.4586	0.4047	0.2646	0.3111	0.4501
Char. path length	0.1246	0.1302	0.0558	0.4798	0.2671	0.2535

Table 228: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.453893	790
MCI	0.411030	790
MCIAD	0.411030	790
AD	0.411030	790

Table 229: pos05nopartnowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.71	0.482	958511.0	0.78	1.64
MCI	1.87	0.379	812979.0	0.69	1.68
MCI-AD	0.51	0.287	809591.0	0.70	1.75
AD	2.73	0.466	776531.0	0.72	1.62

Table 230: Graph metrics: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1221	0.3495	0.0378	0.0861	0.1771	0.0266
Norm. Fiedler	0.2199	0.1015	0.4233	0.2453	0.2665	0.1226
Assortativity	0.0008	0.0007	0.0001	0.4667	0.2145	0.2415
Clustering coefficient	0.0038	0.008	0.0273	0.4002	0.2315	0.3145
Char. path length	0.2602	0.0528	0.4238	0.151	0.2041	0.0332

Table 231: Permutation testing: Positive correlations, binary edges, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.046281	70
MCI	0.072778	131
MCIAD	0.080000	144
AD	0.082236	153

Table 232: pos05nowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.08	0.040	783.0	0.00	4.39
MCI	0.62	0.211	3560.0	0.00	2.94
MCI-AD	0.28	0.156	6653.0	0.00	3.06
AD	0.33	0.192	7024.0	0.00	2.99

Table 233: Graph metrics: Positive correlations, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0615	0.3154	0.2779	0.1181	0.1398	0.443
Norm. Fiedler	0.1156	0.2061	0.1273	0.3474	0.461	0.376
Assortativity	0.3193	0.0467	0.0537	0.0822	0.095	0.4793
Clustering coefficient	0.0	0.0	0.178	0.0	0.1677	0.1707
Char. path length	0.1711	0.166	0.165	0.5158	0.5184	0.5022

Table 234: Permutation testing: Positive correlations, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.045953	67
MCI	0.053825	70
MCIAD	0.084488	61
AD	0.068182	66

Table 235: pos05nowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.06	0.028	700.0	0.00	4.61
MCI	0.15	0.073	892.0	0.00	3.89
MCI-AD	0.13	0.067	1173.0	0.00	3.83
AD	0.15	0.085	1047.0	0.00	3.66

Table 236: Graph metrics: Positive correlations, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.077	0.1272	0.068	0.3541	0.4837	0.3377
Norm. Fiedler	0.0869	0.1132	0.0392	0.4226	0.3419	0.2685
Assortativity	0.2907	0.0196	0.0756	0.0497	0.1782	0.2058
Clustering coefficient	0.0	0.0	0.0	0.0	0.0	0.0
Char. path length	0.2172	0.1671	0.1244	0.4253	0.3415	0.4116

Table 237: Permutation testing: Positive correlations, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.005253	70
MCI	0.008463	131
MCIAD	0.008324	144
AD	0.008387	153

Table 238: pos05wtmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.039	10.3	0.00	15.47
MCI	0.06	0.217	52.3	0.00	21.37
MCI-AD	0.02	0.113	74.9	0.00	20.05
AD	0.03	0.188	74.7	0.00	18.81

Table 239: Graph metrics: Positive correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0862	0.5465	0.3991	0.0853	0.1275	0.3742
Norm. Fiedler	0.0772	0.3641	0.1124	0.1575	0.4045	0.2104
Assortativity	0.3431	0.0945	0.1341	0.1775	0.2288	0.4429
Clustering coefficient	0.0	0.0	0.1762	0.0	0.1665	0.17
Char. path length	0.078	0.1306	0.1817	0.3147	0.2203	0.3856

Table 240: Permutation testing: Positive correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.005273	67
MCI	0.007251	70
MCIAD	0.010210	61
AD	0.007919	66

Table 241: pos05wtmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.025	9.4	0.00	15.20
MCI	0.02	0.078	17.4	0.00	19.80
MCI-AD	0.01	0.056	15.8	0.00	13.55
AD	0.01	0.094	14.4	0.00	14.17

Table 242: Graph metrics: Positive correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0715	0.1649	0.2111	0.2719	0.2358	0.4476
Norm. Fiedler	0.0566	0.1723	0.0169	0.2251	0.2699	0.0848
Assortativity	0.2672	0.271	0.4189	0.464	0.3357	0.3575
Clustering coefficient	0.0	0.0	0.0	0.0	0.0	0.0
Char. path length	0.1567	0.4341	0.4886	0.1192	0.145	0.4365

Table 243: Permutation testing: Positive correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.127417	1756
MCI	0.104063	1580
MCIAD	0.130819	1786
AD	0.126105	1822

Table 244: pos05wtnopartmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.41	0.819	113377.3	0.96	8.60
MCI	1.25	0.655	70746.4	0.90	10.02
MCI-AD	2.16	0.813	121034.9	0.97	8.77
AD	3.36	0.842	112587.5	0.97	8.66

Table 245: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2167	0.4676	0.1552	0.2485	0.05	0.1588
Norm. Fiedler	0.0064	0.5231	0.2362	0.0065	0.0019	0.28
Assortativity	0.1529	0.4082	0.5201	0.1153	0.1598	0.4258
Clustering coefficient	0.0136	0.1248	0.0612	0.0048	0.0025	0.3542
Char. path length	0.0208	0.3968	0.4597	0.0391	0.0298	0.438

Table 246: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.120107	1580
MCI	0.104063	1580
MCIAD	0.123343	1580
AD	0.116365	1580

Table 247: pos05wtnopartmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.34	0.820	110728.5	0.95	8.62
MCI	1.29	0.650	56888.3	0.83	10.19
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 248: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.162	0.3934	0.1996	0.238	0.0391	0.1451
Norm. Fiedler	0.0019	0.3939	0.3738	0.0023	0.0014	0.2898
Assortativity	0.0624	0.3772	0.4626	0.042	0.0792	0.3515
Clustering coefficient	0.0014	0.0075	0.0855	0.0005	0.0008	0.1004
Char. path length	0.0127	0.4017	0.4599	0.0237	0.0168	0.4441

Table 249: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.112504	1422
MCI	0.098177	1422
MCIAD	0.115621	1422
AD	0.108678	1422

Table 250: pos05wtnopartmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.45	0.823	110671.1	0.95	8.62
MCI	1.35	0.664	58982.3	0.84	10.17
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 251: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1522	0.3912	0.2003	0.2299	0.0367	0.1451
Norm. Fiedler	0.0017	0.3852	0.3863	0.0029	0.0014	0.2898
Assortativity	0.0639	0.3772	0.4646	0.0419	0.081	0.3515
Clustering coefficient	0.0013	0.0073	0.0702	0.0007	0.0011	0.1004
Char. path length	0.0127	0.4027	0.4602	0.0241	0.0169	0.4441

Table 252: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.103614	1264
MCI	0.091677	1264
MCIAD	0.106469	1264
AD	0.100179	1264

Table 253: pos05wtnopartmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.41	0.819	110893.5	0.95	8.62
MCI	1.41	0.667	58696.2	0.84	10.17
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 254: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1592	0.3985	0.1978	0.2312	0.0367	0.1451
Norm. Fiedler	0.002	0.3937	0.3775	0.0036	0.001	0.2898
Assortativity	0.0636	0.375	0.4648	0.0427	0.0801	0.3515
Clustering coefficient	0.0013	0.0074	0.0724	0.0007	0.0009	0.1004
Char. path length	0.0129	0.4024	0.4609	0.0239	0.0173	0.4441

Table 255: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.094158	1106
MCI	0.084148	1106
MCIAD	0.096250	1106
AD	0.091361	1106

Table 256: pos05wtnopartmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.41	0.819	110051.7	0.95	8.63
MCI	1.38	0.684	57633.3	0.84	10.18
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 257: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1461	0.3927	0.1999	0.2188	0.0352	0.1451
Norm. Fiedler	0.0019	0.384	0.3833	0.0027	0.001	0.2898
Assortativity	0.0627	0.3754	0.4651	0.0431	0.0808	0.3515
Clustering coefficient	0.0013	0.0075	0.0757	0.0006	0.001	0.1004
Char. path length	0.013	0.4023	0.4599	0.0244	0.0167	0.4441

Table 258: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.084085	948
MCI	0.075486	948
MCIAD	0.085857	948
AD	0.081368	948

Table 259: pos05wtnopartmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.41	0.817	110658.0	0.95	8.62
MCI	1.20	0.662	57517.1	0.84	10.20
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 260: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1567	0.3939	0.1977	0.2298	0.0362	0.1451
Norm. Fiedler	0.0024	0.3913	0.3782	0.0032	0.0016	0.2898
Assortativity	0.0621	0.3768	0.464	0.0417	0.0799	0.3515
Clustering coefficient	0.0011	0.0074	0.0782	0.0008	0.001	0.1004
Char. path length	0.0123	0.4031	0.4632	0.0235	0.0166	0.4441

Table 261: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.080824	790
MCI	0.066005	790
MCIAD	0.074760	790
AD	0.070242	790

Table 262: pos05wtnopartmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	2.45	0.818	110930.7	0.95	8.62
MCI	1.26	0.679	55857.8	0.83	10.25
MCI-AD	2.10	0.808	120299.6	0.96	8.77
AD	3.24	0.828	107837.0	0.96	8.66

Table 263: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1527	0.3885	0.2017	0.2285	0.0366	0.1451
Norm. Fiedler	0.0013	0.3891	0.379	0.0028	0.0009	0.2898
Assortativity	0.0636	0.3783	0.4628	0.0424	0.08	0.3515
Clustering coefficient	0.0012	0.0073	0.0803	0.0006	0.0009	0.1004
Char. path length	0.0128	0.4009	0.4584	0.0235	0.0169	0.4441

Table 264: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.388680	1756
MCI	0.327249	1580
MCIAD	0.430533	1786
AD	0.430900	1822

Table 265: pos05wtnopartnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	11.06	0.828	1059294.6	0.96	2.78
MCI	6.63	0.732	708834.3	0.90	3.08
MCI-AD	12.41	0.795	1306274.8	0.97	2.44
AD	14.14	0.855	1317807.5	0.97	2.44

Table 266: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2656	0.3168	0.1927	0.1497	0.0825	0.3571
Norm. Fiedler	0.0543	0.3125	0.2126	0.1327	0.0149	0.1234
Assortativity	0.1606	0.211	0.1931	0.0431	0.0399	0.4774
Clustering coefficient	0.0139	0.1478	0.0641	0.0054	0.0024	0.326
Char. path length	0.1088	0.079	0.0756	0.0081	0.0067	0.4904

Table 267: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.369316	1580
MCI	0.327249	1580
MCIAD	0.403972	1580
AD	0.398994	1580

Table 268: pos05wtnopartnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	6.49	0.763	915667.9	0.92	2.78
MCI	6.63	0.732	708834.3	0.90	3.08
MCI-AD	7.46	0.697	1077178.2	0.91	2.44
AD	8.77	0.773	1038956.0	0.90	2.45

Table 269: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.4603	0.371	0.2345	0.4138	0.2753	0.3524
Norm. Fiedler	0.1903	0.042	0.4274	0.1977	0.1463	0.0276
Assortativity	0.1507	0.2195	0.28	0.0446	0.0634	0.4332
Clustering coefficient	0.0753	0.3321	0.0228	0.1605	0.3005	0.065
Char. path length	0.0901	0.0607	0.0618	0.0046	0.0047	0.4932

Table 270: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.347595	1422
MCI	0.309256	1422
MCIAD	0.377817	1422
AD	0.372904	1422

Table 271: pos05wtnopartnowgmg.st2

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	4.12	0.715	781671.4	0.89	2.81
MCI	4.37	0.654	606029.0	0.87	3.09
MCI-AD	4.91	0.629	893691.1	0.88	2.47
AD	5.93	0.724	856077.5	0.86	2.47

Table 272: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.448	0.3807	0.2507	0.4369	0.3067	0.3665
Norm. Fiedler	0.088	0.0317	0.4454	0.2991	0.0756	0.0248
Assortativity	0.1391	0.2573	0.3337	0.0494	0.0771	0.4163
Clustering coefficient	0.0673	0.1717	0.0058	0.2831	0.1692	0.0642
Char. path length	0.086	0.0458	0.049	0.0033	0.0032	0.4931

Table 273: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.322714	1264
MCI	0.288126	1264
MCIAD	0.348192	1264
AD	0.343946	1264

Table 274: pos05wtnopartnowgmg.st3

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	1.70	0.665	653503.9	0.85	2.88
MCI	2.50	0.580	498767.3	0.83	3.11
MCI-AD	2.89	0.578	721312.9	0.84	2.52
AD	4.78	0.669	688035.4	0.82	2.52

Table 275: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.3464	0.2907	0.0779	0.439	0.1632	0.2019
Norm. Fiedler	0.0766	0.0669	0.4947	0.4838	0.075	0.0663
Assortativity	0.1163	0.3122	0.4041	0.054	0.0875	0.4044
Clustering coefficient	0.091	0.2877	0.0417	0.222	0.3566	0.1293
Char. path length	0.1019	0.0329	0.0346	0.0027	0.0029	0.4989

Table 276: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.294842	1106
MCI	0.263779	1106
MCIAD	0.315517	1106
AD	0.312205	1106

Table 277: pos05wtnopartnowgmg.st4

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.60	0.509	533318.7	0.82	3.00
MCI	1.49	0.479	396913.4	0.80	3.18
MCI-AD	1.73	0.535	558605.2	0.81	2.59
AD	3.64	0.618	534095.9	0.79	2.58

Table 278: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2741	0.2275	0.0259	0.4426	0.0836	0.1091
Norm. Fiedler	0.3179	0.3769	0.1017	0.2244	0.0684	0.1431
Assortativity	0.0896	0.4074	0.5083	0.065	0.1029	0.4099
Clustering coefficient	0.2216	0.3245	0.0855	0.3779	0.2824	0.1868
Char. path length	0.1537	0.017	0.0173	0.0027	0.0019	0.4882

Table 279: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.264172	948
MCI	0.236776	948
MCIAD	0.280263	948
AD	0.277697	948

Table 280: pos05wtnopartnowgmg.st5

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.22	0.326	412131.3	0.77	3.15
MCI	1.03	0.451	299731.9	0.74	3.25
MCI-AD	0.95	0.497	414478.2	0.76	2.68
AD	3.11	0.548	392819.3	0.76	2.66

Table 281: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1838	0.2082	0.0026	0.4401	0.019	0.0176
Norm. Fiedler	0.1596	0.1073	0.069	0.318	0.192	0.2976
Assortativity	0.0705	0.4884	0.3934	0.0745	0.1235	0.3957
Clustering coefficient	0.2295	0.3914	0.3804	0.3219	0.3369	0.489
Char. path length	0.267	0.0106	0.0099	0.0038	0.0025	0.4569

Table 282: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.254641	790
MCI	0.207128	790
MCIAD	0.242171	790
AD	0.240314	790

Table 283: pos05wtnopartnowgmg.st6

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.33	0.478	312157.0	0.79	3.08
MCI	0.82	0.354	213982.3	0.70	3.37
MCI-AD	0.27	0.278	285773.6	0.71	2.94
AD	1.40	0.457	272199.3	0.73	2.76

Table 284: Graph metrics: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1646	0.3974	0.0365	0.1312	0.1249	0.0301
Norm. Fiedler	0.1824	0.095	0.4097	0.2774	0.2287	0.1202
Assortativity	0.0365	0.3074	0.2296	0.103	0.1534	0.4063
Clustering coefficient	0.0038	0.0053	0.0248	0.4571	0.2576	0.29
Char. path length	0.0865	0.2996	0.1007	0.0343	0.0054	0.2326

Table 285: Permutation testing: Positive correlations, correlation weighted, ordinary Pearson, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.015428	70
MCI	0.025363	131
MCIAD	0.028167	144
AD	0.028104	153

Table 286: pos05wtnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.02	0.032	87.0	0.00	13.49
MCI	0.19	0.206	442.8	0.00	8.28
MCI-AD	0.09	0.157	846.0	0.00	8.61
AD	0.10	0.176	850.1	0.00	8.45

Table 287: Graph metrics: Positive correlations, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0792	0.3098	0.3196	0.1544	0.1569	0.4926
Norm. Fiedler	0.0947	0.1545	0.1322	0.3676	0.4064	0.4528
Assortativity	0.3184	0.0375	0.0532	0.066	0.0932	0.5513
Clustering coefficient	0.0	0.0	0.1772	0.0	0.1669	0.1704
Char. path length	0.1591	0.1418	0.1504	0.5525	0.5255	0.5308

Table 288: Permutation testing: Positive correlations, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.015477	67
MCI	0.021322	70
MCIAD	0.035435	61
AD	0.027328	66

Table 289: pos05wtnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.02	0.024	79.7	0.00	13.99
MCI	0.06	0.071	140.3	0.00	9.76
MCI-AD	0.05	0.066	210.5	0.00	8.90
AD	0.06	0.088	175.2	0.00	8.92

Table 290: Graph metrics: Positive correlations, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.0788	0.1385	0.082	0.3287	0.4732	0.353
Norm. Fiedler	0.0827	0.0947	0.0232	0.4444	0.2587	0.2116
Assortativity	0.2551	0.0111	0.0563	0.0256	0.1479	0.1291
Clustering coefficient	0.0	0.0	0.0	0.0	0.0	0.0
Char. path length	0.2119	0.0945	0.1136	0.2445	0.289	0.443

Table 291: Permutation testing: Positive correlations, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

A.3 Negative Correlations

Population	Average Weight	Num. Edges
Normal	0.029405	35
MCI	0.022188	75
MCIAD	0.020855	86
AD	0.020844	92

Table 292: neg05mg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.015	39.2	0.12	12.44
MCI	0.04	0.044	113.1	0.25	12.74
MCI-AD	0.01	0.006	203.2	0.31	16.80
AD	0.04	0.036	180.9	0.28	13.75

Table 293: Graph metrics: Negative correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1098	0.5523	0.1122	0.122	0.4753	0.1182
Norm. Fiedler	0.0953	0.6065	0.1311	0.1086	0.3905	0.1531
Assortativity	0.5481	0.1578	0.2554	0.1534	0.2445	0.3553
Clustering coefficient	0.3733	0.1819	0.2778	0.2698	0.381	0.3814
Char. path length	0.7782	0.5217	0.7189	0.1703	0.4026	0.2464

Table 294: Permutation testing: Negative correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.049888	21
MCI	0.045977	18
MCIAD	0.051051	15
AD	0.040721	20

Table 295: neg05mg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.05	0.089	23.5	0.22	6.97
MCI	0.03	0.041	17.9	0.24	7.92
MCI-AD	0.05	0.079	9.9	0.13	6.39
AD	0.02	0.034	14.4	0.21	8.57

Table 296: Graph metrics: Negative correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2141	0.5247	0.2044	0.2565	0.4776	0.2462
Norm. Fiedler	0.191	0.3722	0.1756	0.2928	0.4618	0.2705
Assortativity	0.2507	0.0926	0.1671	0.2523	0.3865	0.3513
Clustering coefficient	0.5765	0.2048	0.3348	0.2912	0.4437	0.3342
Char. path length	0.3309	0.4806	0.2752	0.2954	0.4208	0.247

Table 297: Permutation testing: Negative correlations, binary edges, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.089286	35
MCI	0.070888	75
MCIAD	0.071637	86
AD	0.070742	92

Table 298: neg05nowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.05	0.024	428.0	0.12	4.31
MCI	0.14	0.048	1148.0	0.25	3.93
MCI-AD	0.02	0.007	2540.0	0.31	4.96
AD	0.13	0.037	2225.0	0.28	4.07

Table 299: Graph metrics: Negative correlations, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1024	0.5323	0.1065	0.1056	0.4559	0.105
Norm. Fiedler	0.1147	0.5508	0.1856	0.101	0.3423	0.1581
Assortativity	0.4994	0.0713	0.1371	0.0779	0.1446	0.3054
Clustering coefficient	0.3778	0.1843	0.2966	0.265	0.398	0.3618
Char. path length	0.2085	0.5643	0.2404	0.2191	0.4692	0.2485

Table 300: Permutation testing: Negative correlations, binary edges, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.164062	21
MCI	0.140625	18
MCIAD	0.177515	15
AD	0.123457	20

Table 301: neg05nowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.14	0.083	285.0	0.23	2.88
MCI	0.10	0.048	147.0	0.23	3.27
MCI-AD	0.22	0.138	143.0	0.14	2.74
AD	0.08	0.038	140.0	0.21	3.95

Table 302: Graph metrics: Negative correlations, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2649	0.3068	0.2127	0.1788	0.4268	0.1452
Norm. Fiedler	0.2314	0.2646	0.204	0.1448	0.4481	0.1251
Assortativity	0.0373	0.0379	0.0335	0.4902	0.4753	0.4731
Clustering coefficient	0.6007	0.2068	0.329	0.3205	0.4635	0.3454
Char. path length	0.2942	0.5324	0.144	0.3122	0.2788	0.1527

Table 303: Permutation testing: Negative correlations, binary edges, partial correlations, no extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.008723	35
MCI	0.007274	75
MCIAD	0.006934	86
AD	0.006768	92

Table 304: neg05wtmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.00	0.015	3.6	0.12	5.68
MCI	0.01	0.042	12.3	0.25	11.34
MCI-AD	0.00	0.006	23.4	0.31	11.17
AD	0.01	0.036	20.0	0.28	11.14

Table 305: Graph metrics: Negative correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1076	0.5502	0.1165	0.1213	0.4524	0.1229
Norm. Fiedler	0.0988	0.6088	0.1321	0.1139	0.4125	0.1524
Assortativity	0.5389	0.1307	0.2354	0.1277	0.2325	0.3189
Clustering coefficient	0.3817	0.1796	0.2718	0.2578	0.3608	0.3849
Char. path length	0.5878	0.4736	0.5432	0.5986	0.5395	0.437

Table 306: Permutation testing: Negative correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.015483	21
MCI	0.017315	18
MCIAD	0.019457	15
AD	0.015420	20

Table 307: neg05wtmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.091	2.3	0.22	3.02
MCI	0.01	0.042	2.5	0.24	4.47
MCI-AD	0.02	0.089	1.5	0.14	2.99
AD	0.01	0.036	2.1	0.21	4.38

Table 308: Graph metrics: Negative correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2045	0.4414	0.1911	0.2153	0.4803	0.2084
Norm. Fiedler	0.1783	0.3918	0.1658	0.2597	0.4683	0.2459
Assortativity	0.6987	0.1109	0.2082	0.3027	0.416	0.3764
Clustering coefficient	0.5776	0.2076	0.3328	0.2968	0.4425	0.3417
Char. path length	0.2738	0.4169	0.2924	0.2119	0.4861	0.228

Table 309: Permutation testing: Negative correlations, correlation weighted, partial correlations, CT thickness used for extra edge weighting, sparsity fixed

Population	Average Weight	Num. Edges
Normal	0.026635	35
MCI	0.023212	75
MCIAD	0.024113	86
AD	0.022934	92

Table 310: neg05wtnowgmg

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.01	0.024	40.2	0.13	9.19
MCI	0.04	0.046	124.9	0.25	12.16
MCI-AD	0.01	0.007	303.6	0.32	14.76
AD	0.04	0.036	246.1	0.28	12.63

Table 311: Graph metrics: Negative correlations, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.1021	0.5298	0.1109	0.105	0.434	0.1133
Norm. Fiedler	0.1212	0.5501	0.1885	0.1049	0.3531	0.1597
Assortativity	0.4896	0.0517	0.1258	0.0563	0.1367	0.2267
Clustering coefficient	0.3857	0.1803	0.2881	0.255	0.3805	0.3659
Char. path length	0.7076	0.503	0.66	0.2174	0.4372	0.2774

Table 312: Permutation testing: Negative correlations, correlation weighted, partial correlations, no extra edge weighting, no control on number of edges

Population	Average Weight	Num. Edges
Normal	0.050993	21
MCI	0.053324	18
MCIAD	0.069505	15
AD	0.046651	20

Table 313: neg05wtnowgmg.st

Group	Fiedler	Norm. Fiedler	Assort.	CC	L_p
N	0.04	0.085	28.4	0.23	5.41
MCI	0.04	0.048	21.0	0.23	6.44
MCI-AD	0.09	0.152	23.1	0.15	5.39
AD	0.03	0.041	20.2	0.21	7.07

Table 314: Graph metrics: Negative correlations, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

Metric	N vs. MCI	N vs. MCIAD	N vs. AD	MCI vs. MCIAD	MCI vs. AD	MCIAD vs. AD
Fiedler	0.2634	0.2383	0.2052	0.141	0.4323	0.1182
Norm. Fiedler	0.2124	0.2469	0.1952	0.1191	0.4613	0.1095
Assortativity	0.0702	0.1207	0.0678	0.3812	0.5036	0.3726
Clustering coefficient	0.6015	0.208	0.3271	0.3263	0.4633	0.3522
Char. path length	0.3582	0.4806	0.2732	0.3301	0.3938	0.2492

Table 315: Permutation testing: Negative correlations, correlation weighted, partial correlations, no extra edge weighting, sparsity fixed

B Regression Investigation Results

	AGE	PTGENDER	PTEDUCAT	MCI	AD	MCIAD
# SIG<.05	62	20	48	35	65	66
# SIG<.1	65	25	55	41	65	66

Table 316: Regression containing individual terms for age, gender, education level, and diagnostic group.

	AGE	PTGENDER	MCI	AD	MCIAD
# SIG<.05	63	53	38	65	65
# SIG<.1	64	58	45	65	66

Table 317: Regression containing individual terms for age, gender, and diagnostic group.

	AGE	PTEDUCAT	MCI	AD	MCIAD	PTEDUCAT:PTGENDER
# SIG<.05	61	54	35	65	66	17
# SIG<.1	65	59	42	65	66	26

Table 318: Regression containing individual terms for age, gender, and diagnostic group with a term for the interaction between education level and gender.

	AGE	PTEDUCAT	MCI	AD	MCIAD	AGE:MCI	AGE:AD	AGE:MCIAD
# SIG<.05	30	52	0	15	3	0	9	3
# SIG<.1	39	59	0	20	7	2	15	6

Table 319: Regression containing individual terms for age, education level, and diagnostic group with terms for the interaction between age and diagnostic group.

	AGE	PTEDUCAT	PTGENDER	MCI	AD	MCIAD	AGE:PTGENDER
# SIG<.05	53	48	12	30	65	66	13
# SIG<.1	57	55	19	41	65	66	21

Table 320: Regression containing individual terms for age, education level, gender, and diagnostic group with a term for the interaction between age and gender.

	AGE	PTEDUCAT	PTGENDER
# SIG<.05	57	22	20
# SIG<.1	59	29	26

Table 321: Regression containing individual terms for age, education level, and gender.